

CAN VOLATILITY BASED TECHNICAL SIGNALS CAPTURE CONSISTENT
ABNORMAL EQUITY INDEX RETURNS?

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THESIS

Submitted in partial fulfillment of the requirements
for the degree of Master of Science in Agricultural and Applied Economics
in the Graduate College of the
University of Illinois at Urbana-Champaign, 2016

Urbana, Illinois

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ABSTRACT

This thesis examines a combined technical signal approach (CSA) on four stock index implied volatility indices for the aim of day trading the underlying stock indices. The purpose is to determine whether excess returns derived from the use of a combined technical trading strategy are statistically significantly different than zero. The null hypothesis is that the average daily rate of excess return of the strategy, for every underlying stock index is zero; the alternative hypothesis is that the average daily rate of excess return of the strategy, per equity index, is different than zero, both before and after trading costs and dividends are considered. A two-tailed z test is utilized to test the statistical significance of the difference between the annualized mean daily rate of excess return of the day trading strategy and zero. For every implied volatility index, all available data is utilized to determine the persistence of excess returns over a robust timeframe, the total available sample period. White's Reality Check Test is applied to each excess return series, first by utilizing the moving blocks bootstrapping method, to determine whether mean excess returns are statistically significantly different than zero, regardless of the shapes of the original distributions of excess returns. This research also tests whether each distribution of excess returns for each of the four daily traded stock indices conforms to a normal distribution using the Jarque-Bera goodness of fit to normality test, before and after transaction costs and dividends are considered. Three different trading strategies are compared: a volatility based CSA that utilizes the momentum approach to day trading, an equity based CSA that utilizes the mean reversion approach to day trading, and a buy and hold approach. A final measure of performance, the Sharpe Ratio, is utilized in order to determine which strategy has the highest risk adjusted returns.

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CHAPTER 1

INTRODUCTION

1.1 OBJECTIVES

The purpose of this thesis is to determine if using a Combined Technical Signal Approach on the implied volatility indices of specific stock indices can generate persistent abnormal returns to day-trading those indices. This analysis is conducted on the S&P 500, S&P100, DJIA, and the NASDAQ Composite and their corresponding implied volatility indices, VIX, VXO, VXD, and VXN. The ability to generate persistent abnormal returns would validate both technical analysis and the use of implied volatility indices as tools for forecasting. Day trading US equity indices using implied volatility index based technical signals has the potential to capture consistently positive excess returns against a buy and hold strategy of the same US equity indices. Determining the shape and consistency of each excess return distribution will verify whether excess returns conform to a zero mean, normal distribution, as proposed by Jensen (1968).

1.2 RESEARCH JUSTIFICATION

The utilization of volatility indices as predictive tools to capture persistent returns via day trading the underlying stock indices is justified because of the way the volatility indices are constructed. Each volatility index is a volume-weighted summation of the implied volatilities on all outstanding stock index option contracts; VXO uses the original formula by only using at-the-money option contracts, which will expire within approximately thirty days. Plainly speaking, these volatility indices measure the annualized expected change in price of their respective stock index over the next thirty days. This makes volatility indices a leading indicator, which may give the VIX and its cohorts predictive insight into daily market trends. Implied Volatility, as

constructed from underlying options contracts is in essence an aggregate sentiment of demand for put contracts. According to a file in the CBOE's archive entitled, *CBOE S&P500 Index (SPX) Volume and Put/Call Ratio Archive*, from 09/27/1995 to 12/31/2014, on average approximately sixty-three percent of total S&P500 option contracts traded are put contracts. Since put options operate as a form of stock market insurance, the VIX and its sister indices, as they are constructed from the implied volatility of the options market, mostly reflect demand for put contracts, which coincides with price moving down. Therefore, the VIX and its cohorts move contrarian to the stock market, gaining when stocks decline and vice versa. In other words, implied volatility indices are the perfect hedging indicator regarding their underlying equity indices. Figure 1 below illustrates the inverse relationship each equity index has with its corresponding implied volatility index. Utilizing implied volatility to indicate potential market direction is relatively a novel concept to the world of technical analysis, but this research offers the most comprehensive study of not just the infamous VIX, but several volatility based indices, in order to fully gauge the capability of volatility as a predictor of market movement. The motivation of this study is to both develop a profitable day trading strategy and ascertain the validity of numerous volatility indices as crystal balls of price movement, which would help to confirm that the technical analysis approach to forecasting stock market movements is a viable method of generating alpha.

1.3 METHODS

Creating buy/sell signals on a daily basis for each of the four stock indices is accomplished by utilizing a Combined Technical Signal Approach (CSA). The CSA follows a simple majority voting process. The signals within the combined signal offer one buy/sell "vote" per trading day, a long direction in the underlying stock index is taken when the majority of "votes" register a

buy signal, and vice versa. The Combined Signal Approach utilizes three different technical signals: simple moving average, filter rule, and trading range break out, each technical signal is applied three times by changing the signal's parameters, for a total of nine technical signals. For example, three different simple moving averages are taken using the 50, 150, and 200 prior trading days. The logic behind the combined approach is the notion of confirmation. Directional signals should confirm one another before a decision is made.

Technical analysis is divided between two approaches: momentum based trading and mean reversion based trading. Each signal in the CSA can be modified to fit either trading strategy. For example, if the opening price of a volatility index is greater than an x day moving average, according to momentum theory, volatility is expected to rise. According to mean reversion theory, volatility would be expected to fall in the given scenario. In this research, the volatility based CSA utilizes a momentum based approach, while the equity based CSA utilizes a mean reversion based approach. Both momentum and mean reversion theory are applied to both volatility and equity based CSA trading strategies, initially. The reason that the volatility based CSA utilizes momentum theory and the equity based CSA uses mean reversion theory is that the volatility based CSA that used momentum theory outperformed the volatility based CSA that used mean reversion theory, while the equity based CSA that used mean reversion theory outperformed the equity based CSA that used momentum theory. Thus the performances of the volatility based CSA trading strategy that utilizes the mean reversion approach to day trading and the equity based CSA trading strategy that uses the momentum approach to day trading are not presented in the research.

Once the excess return series for each stock index is established against each stock index's respective buy and hold return series, a bootstrap simulation is initiated per White's Reality

Check Test, White (2000). White's Reality Check Test is applied in this research to uncover whether statistically significant excess returns are persistent or merely coincidental. White's Reality Check Test is utilized to determine the statistical significance of each excess return series, regardless of whether or not excess returns conform to a normal distribution. The moving blocks method is a bootstrapping technique that is appropriate for dependant data, such as time series data. The moving blocks method of bootstrapping takes subsequent observations from the original time series and uses them as building blocks which are then randomly re-sampled with replacement in order to create simulations of the original time series. The bootstrapping process is necessary for transforming a random, non-normal, variable into a normally distributed random variable, for the purpose of determining statistical significance by utilizing the two-tailed z test, which is only applicable for normally distributed random variables. The mean of simulated means and mean of simulated standard deviations of the bootstrap generated samples is computed in order to calculate, via a two tailed z test, whether excess returns are statistically significant, before and after dividends and transaction costs are considered. The Jarque-Bera goodness of fit to normality test is utilized to determine if each excess return series generated from day trading the equity indices is consistent with the normal distribution, as assumed in the academic literature.

The statistical significance of each strategy's Sharpe Ratio is acquired through the same moving block bootstrapping process, each simulated time series yields one Sharpe Ratio, the average and standard deviation of all the Sharpe Ratios for a given set of time series simulations conform to a normal distribution, a two-tailed z statistics test is applied to determine the significance of the excess Sharpe Ratio, the Sharpe Ratio of the highest yielding trading strategy minus the Sharpe Ratio of the buy and hold strategy.

CHAPTER 2

BACKGROUND

Technical Analysis is one of the two schools of thought for investors who hope to gain an edge when trading in the equity markets, the other being Fundamental Analysis. Both technical and fundamental analysis utilize key signals to determine the likely direction of a financial security, hoping to gain monetary compensation for their proper judgment as to the asset's fair value. The major difference between the two schools that investors employ is where the signals originate. Technical Analysis signals originate predominately from price, volume, and open interest of the underlying security, whereas Fundamental Analysis signals originate from, mostly, quarterly financial statements and widely monitored macroeconomic indicators. This research focuses on the technical school of thought, harkening back to ticker tape traders who would wait for price movements to confirm volume signals, in a way, the very first combined signal approach. As the old adage goes, volume moves before price, and change in price confirms the change in volume. The notion of combining technical based signals became popular in the 1980's due to technical analyst John Bollinger and his Bollinger Bands. A simple moving average of historical price combined with a simple moving average of historical volatility creates a sort of support and resistance price band, and when combined with volume, a useful indication of market reversals and breakthroughs. The evolution of combined technical signals further progressed after the beginning of the new millennium due to author Camillo Lento and his Combined Technical Signal Approach.

The Combined Technical Signal Approach is a method of technical analysis, which combines several technical signals and arose through the academic findings of Lento and

Gradojevic (2007). Authors Camillo Lento and Nikola Gradojevic (2007) test the ability of a so-called Combined Signal Approach, CSA, as a daily buy/sell equity index indicator, for the NASDAQ, DJIA, and the TSX 300. The CSA is composed of a total of nine indicators: three simple moving averages, the 50, 150, and 200 day simple moving averages, three different filter rules at 1, 2, and 5% and three trading range break out indicators, which look back 50, 150, and 200 trading days. The authors conclude that consistent abnormal profit beats a naive buy and hold strategy, can be generated when two out of the nine indicators agree to either buy or sell on a particular trading day. Subsequently, Lento wrote several other papers, his most famous being, A Combined Signal Approach to Technical Analysis, in 2008, in which the Combined Signal Approach, the same one applied in his 2007 paper, was tested and verified as a successful daily directional buy/sell indicator for the S&P 500 equity index. In fact, Lento went on to write two more papers, one in 2009, and one in 2010, where he applies and confirms the predictive power of the CSA on 8 separate equity indices in the Asian-Pacific equity markets and the Athens Stock Exchange General Index respectively. In all cases the track record is quite clear, the Combined Signal Approach is a successful tool in generating excess returns from equity indices. Perhaps, implied volatility derived technical signals combined with Lento's approach produces similar results with regards to capturing anomalous stock returns.

CHAPTER 3

LITERATURE REVIEW

The literature regarding technical analysis is quite extensive. Thousands of years ago, the Ancient Egyptian priesthood, with the aid of what is known as a nilometer, were able to forecast the health of the flow of the Nile in preparation for both farming and tax collection, this nilometer is no doubt an example of technical analysis using historical data, which goes back thousands of years. A low reading on the nilometer forecasted famine the year ahead, an average reading, an abundant harvest, and a high reading forecasted over flooding. In the eighteenth century, a Japanese rice merchant and futures trader, Homma Munehisa, wrote the first ever book on market psychology, *The Fountain of Gold – The Three Monkey Record of Money* (1755), Homma was also the inventor of the candlestick chart, a staple of modern technical analysis, as well as an advocate of the usefulness of both weather forecasting and volume in predicting price movements.

In the nineteenth century, Charles Dow, father of the Dow Jones Industrial, Transportation, and Utility Averages, and founder of the Wall Street Journal, established Dow Theory. Charles Dow never called his theory Dow Theory, nor did he ever write a book on the subject, although Dow did publish numerous articles and editorials that focus on forecasting price through price charts. Dow Theory was only called Dow Theory after the death of Charles Dow. Researchers William Hamilton in his book, *The Stock Market Barometer* (1922), S.A. Nelson, *The ABC of Stock Speculation* (1930), and Robert Rhea in his book, *The Dow Theory* (1932), refined, articulated, and compiled Dow's theory into a comprehensive "school of thought". Dow Theory has three main tenants. All relevant information regarding a stock is

contained within the current price; therefore the price chart serves as the staple of investment decision-making. Price follows trends. Lastly, trends exist and price will continue to follow the trend until the trend is broken, at which time the price pivots away from the former trend. Essentially, all of Charles Dow's theory is a compilation of momentum strategy. The technical signals utilized by Lento's Combined Signal Approach are derived from Dow Theory: simple moving averages, filter rules, and trading range break out rules are all derived from the momentum strategy inspired by Charles Dow. For example, adherents of Dow Theory consider simple moving averages to be visualizations of trend lines, thus simple moving averages indicate when a price is moving with a trend, or against a trend if the price breaks the trend line. The Filter Rule is another idea borrowed from momentum strategy, which conceptualizes support and resistance levels as respective boosters or containers of price levels. The Filter Rule's support and resistance levels are merely the previous day's high and low prices. The Trading Range Break Out Rule is another application of momentum strategy, which expands upon the filter rule, namely that if the long term support or resistance level is broken, a new dominant trend must have emerged. Dow and his acolytes' focus almost exclusively on signal confirmations, in other words, technical signals are enhanced when one signal confirms another. Interestingly, technical signal confirmation is the foundation of Camillo Lento's combined signal approach, illustrating that a relatively new and successful technical trading strategy is at least in part derived from Charles Dow's well-established concepts. The contribution of Charles Dow to technical analysis via over two hundred fifty papers on the subject during the 19th century would largely remain in the academic dark until the latter half of the 20th century.

There are only a handful of researchers during the first half of the twentieth century who publish work regarding the subject of technical analysis. William Gann, the son of a cotton

farmer, wrote several books on the subjects of both technical analysis and financial astrology for both the commodity and stock market: Truth of The Stock Tape (1923), Tunnel Thru The Air (1927), Wall Street Stock Selector (1930), New Stock Trend Detector (1936), Face Facts America (1940), How To Make Profits In Commodities (1941), 45 Years in Wall Street (1949), The Magic Word (1950), WD Gann Economic Forecaster (1954), and How To Make Profits Trading Puts and Calls (1955). Without going into detail, Gann's work focuses on utilizing simple geometry, drawing several angles from either a local top or bottom to predict support and resistance levels going forward. Gann also utilized what is known as financial astrology to make his predictions, focusing on moon phases, long-term cycles, and planet positions to forecast market movement. While many academics scoff at the notion of astrology as a science, William Gann's success as a trader is nothing to scoff at. Richard Wyckoff, columnist for the Ticker and Investment Digest magazine, claimed to have personally seen Gann make two hundred eighty-six transactions in the month of October 1909, ninety-two percent of these transactions would turn out to be profitable. Not only were two hundred sixty-four transactions profitable, but also in that single month, Gann managed to net one thousand percent profit! Wyckoff later noted regarding William Gann, "Gann can compound money faster than any man I have ever met".

Richard William Schabacker, editor for Forbes magazine wrote three books on the subject of technical analysis: Stock Market Theory and Practice (1930), Technical Analysis and Stock Market Profits (1932), and Stock Market Profits (1934) detailing not only the mechanics of the US equity markets, but also the patterns which technical analysts depend upon for their forecasts. Robert Edwards, a nephew of Schabacker, together with John Magee wrote what is commonly dubbed the bible of technical analysis, Technical Analysis of Stock Trends (1948). A book, which details the pros and cons of Dow Theory, expanding upon what Schabacker wrote

over a decade prior to include an in depth testing of widely used technical signals, their accuracy and profitability across both the equity and commodity markets. While none of the aforementioned researchers applied today's level of statistical scrutiny to their results, it is difficult to disregard their profitability as traders with just dumb luck.

The academic literature regarding technical analysis does not seriously begin until after the first half of the twentieth century. Harry Roberts (1959), while studying technical analysis, concluded that no pattern he studied yielded results that consistently yield profit, more so than mere chance would dictate. Roberts hinted that market prices move randomly up and down, though he was not the first to come up with the notion of the random walk. Louis Bachelier (1900) was the first to model stock prices as stochastic processes, and was the first to liken a stock price's movement to a random walk. The idea that stock prices follow a random walk through time resists the notion that technical analysis can predict market movements better than chance. The random walk model remains the only serious obstacle that technical analysts must overcome to prove the forecasting power of their technical signals. The only way this is possible is by determining the statistical significance of excess returns one derives from his/her trading strategy. If it can be proven that excess returns are statistically significantly different than zero, then the excess returns are generated not due to chance, but because of the skill present within the signal(s)/strategy. The following technical analysis research papers, excluding Lento & Kozyra (2011), have all been catalogued on the University of Illinois's farmdoc website as a summary of the academic research that has been done in the field of technical analysis.

The first comprehensive technical trading research paper written by a serious academic, who studied over 700 technical signals in the copper futures market, goes back to Donchian (1960), the so called father of trend following. Donchian notably founded his own technical

signal, The Donchian Channel, a method for deducing long and short positions, similar to the more modern Bollinger Bands. This Donchian Channel, when applied to the copper futures market was able to generate annualized returns of 39% and 248% for the years 1959 and 1960 respectively. However, Donchian's returns were not compared to any benchmark return series, and Donchian's returns are levered up, generated via a margin account. Going forward, technical analysts and academics researching the subject always: compare their results against a benchmark return series, usually a buy and hold strategy, determine the statistical significance of their excess returns, and ensure that the data mining process is statistically unbiased. This process is the standard approach utilized today to testing the success of technical analysis.

Alexander (1961) compared a day trading strategy against a buy and hold strategy for two stock indices: the S&P Industrials Index, and the Dow Jones Industrial Average. The day trading strategy utilized eleven separate filter rules, finding that three out of the eleven generated consistent excess returns over a buy and hold strategy, however no transaction costs are considered in this work, and no question as to whether excess returns are statistically significant is mentioned. Alexander concluded from his study that stock market price movements exhibit short-term trends aside from the dominant long-term positive trend. A few years later, Alexander would continue his research into the technical analysis of major US Industrial stocks, the next time around, he applies a more realistic assessment of commissions to his research.

Houthakker (1961) compared two benchmark strategies against a day trading strategy in the wheat and corn futures market. The benchmark strategies were buy and hold and sell and hold, while the day trading strategy employed stop-loss orders placed at ten percent intervals from the acquired price of the futures contract. Eleven stop-loss orders, to be precise were compared against Houthakker's two benchmarks, illustrating that both long and short

transactions with a stop loss placed at either ten, twenty, thirty, forty, or fifty percent away from the acquired price of the futures contract yield excess returns over either benchmarks. While short transactions with the same stop loss set up fair slightly worse off than long transactions. Houthakker concluded that the wheat futures market exhibited a seasonal element of “non-randomness” which could be exploited over either benchmark strategies.

Cootner (1962) compared a weekly technical trading strategy consisting of forty-five widely held NYSE stocks against a buy and hold strategy of those same stocks over a five year period. The technical signal utilized by Cootner was a two hundred day simple moving average with a five percent band about the average. Cootner applied a transaction cost to his strategy of one percent per one-way transaction. The band above and below the moving average served as a buy/sell indicator, if the price was above the high band, buy the underlying, if the price was below the low band, sell the underlying. Cootner concluded that neither a buy and hold strategy nor a technical trading strategy employing a simple moving average generated consistent excess returns over the other. However, by utilizing a simple moving average, the variance in returns was lowered by thirty percent compared to a buy and hold strategy. Cootner’s research demonstrated that a technical trading strategy applied to the equity markets could capture higher risk adjusted returns than a naïve buy and hold approach.

Grey and Nielsen (1963) continue the work of Houthakker in the wheat futures market, applying a longer, more robust sample period with which to test his original stop-loss strategy. Again, the authors compare a day trading strategy based off of stop-loss orders against two benchmarks, buy and hold and sell and hold. The authors conclude that Houthakker’s results were biased due to post-WWII government loan programs inducing exploitable seasonality to the wheat futures market in the US during the time of Houthakker’s research. The non-randomness

in Houthakker's results it seems was caused by government intervention in the wheat market, not because the wheat market was itself predictable. Grey and Nielsen discovered a fundamental truth regarding the nature of the markets that is elements of non-randomness are present in markets where central planners/government intervenes.

Government intervention in a market is just as applicable today as it was over five decades ago, with today's low interest rate environment coupled with quantitative easing being the fundamental driver for higher stock prices. Historically, however intervention in the equity markets is more infrequent than intervention in either commodity or foreign exchange markets. As equity markets are mostly allowed to operate through the influence of both retail, but mostly institutional traders. The only time in recent history where government intervention was directly felt in the US equity markets was in the eighty billion dollar government bailout of the automobile industry: GM, Ford, and Chrysler, which was an effort to restore consumer confidence in the American Economy. Whereas, both commodity and foreign exchange markets have a history of frequent government intervention: crop insurance programs, export subsidies, price floors and ceilings, price supports and purchasing of buffer stocks, for example, all serve to stabilize agricultural based futures prices. The Federal Reserve Bank in New York has a history of purchasing US dollars and selling foreign currencies in order to strengthen a perceivably weakening dollar, thereby stabilizing the foreign exchange markets. Perhaps frequent government or central bank intervention has added elements of non-randomness to both the commodity markets and foreign exchange markets that may explain why the success of technical signals is so different in either the commodity or forex markets on the one hand versus equity markets on the other. Profitable technical signals that work in either the commodity or forex markets are most often times useless in the equity markets at capturing consistent economic

profit.

Alexander (1964) again looks at day trading the S&P Industrial Index, however this time around, Alexander compares several different technical trading rules against a buy and hold strategy, while also considering a hefty two percent round-trip transaction cost. Alexander not only analyzes several different filter rules, but also compares different moving averages, and several other Dow Theory inspired technical signals. Alexander concluded that after transaction costs were considered, only one filter rule captured returns consistently over a buy and hold strategy. While all other signals fared worse than a naïve buy and hold strategy.

Smidt (1965) compared a day trading strategy for May soybean futures contracts against a zero mean benchmark, utilizing a transaction cost of thirty-six cents per bushel per round-trip. The specific technical signals that Smidt analyzed belong to the family of momentum oscillators. Momentum oscillators indicate whether a security is overbought or oversold by analyzing recent gains/losses within a specific timeframe. By comparing different time frames, Smidt discovered that seventy percent of all momentum oscillators considered, after transaction costs, captured consistently positive returns. Half of the signals were able to generate an average annualized rate of return of seven and one half percent, even after commissions. The general outperformance of technical signals against a given benchmark within either the agricultural commodity markets or forex markets, while the same technical signals fair much worse when applied to the equity markets has not gone unnoticed.

Both academics and speculators have noticed throughout the years that technical signals seem to capture positive returns more consistently in both the agricultural commodities markets and foreign exchange markets rather than in the equity markets. Many postulate that due to relatively frequent government/central bank intervention within both forex and commodities

markets, that these markets are somewhat less efficient than the equity markets, which are not as influenced by government/central bank intervention, and therefore equity markets are more efficient, being somewhat more random than other markets, which would make equity markets less susceptible to technical analysis than other markets. In the equity markets, before the 1990's, only the relative strength indicator and certain filter rules have been able to "beat" the market, and of all the aforementioned signals, only one, a simple moving average, consistently yields higher risk-adjusted returns than a buy and hold strategy. With this in mind, it is no surprise as to why Lento utilizes both filter rules and simple moving averages as components in his combined signal approach, since both signals have shown a history of some form of success regarding day trading the equity markets.

Fama (1965) analyzed a time series of several stock prices, showing that current prices are uncorrelated to historical prices, measured from the closing price at time t compared to the closing price at time $t-1$, $t-2$, $t-3$, etc. Fama concluded that the only explanation for any change in a stock's price is the random walk hypothesis. Since Fama argued on behalf of the random walk hypothesis, he set the standards by which technical analysis research was to be conducted going forward. In order for technical analysis to be taken seriously, results are expected to yield statistically significant economic profit that cannot be explained by chance alone. Fama did not throw all of technical analysis out the window with his discovery, quite the contrary; Fama's '65 paper merely raised the bar for serious technical analysis in the future. Fama (1966) utilized filter rules to trade the components of the DJIA. Fama discovered that only four out of thirty securities, after transaction costs, yielded statistically significant excess returns. However, once dividends were considered, all variations of the filter rule failed to consistently outperform a naïve buy and hold strategy.

Levy (1967) traded the two hundred components of the NYSE in order to determine a meaningful way to extract statistically significant economic profit by timing the market. Levy compared three rank methods for the stocks he examined. First, Levy looked at each security's relative strength, theorizing that a stock, because of momentum and market participants, will continue in the general direction in which it has been trending. Essentially, Levy believed that stocks, which had recently been outperforming other stocks, are the best stocks to buy, while stocks, which are underperforming their peers, are the best stocks to sell. Levy also attempted to time the market using divergence. Levy assumed that stocks move randomly about their trend line, and when a security diverged significantly from its 26-week simple moving average, that the stock price would revert back to the trend line allowing for predictable economic profit to be realized. Lastly, Levy ranked securities in deciles determined by their historical volatility, believing that more volatile stocks offer higher potential returns. Levy discovered however, that historical volatility is not useful in predicting future returns because, "prospective risk may not be a function of historical risk". Levy's assumptions however proved ineffective at overcoming the returns generated by a buy and hold strategy. Levy concluded "only when a technical investment strategy can produce profits which are superior to those attainable by random selection, at risk which is less than that of random selection, can the random walk hypothesis be disproven". Therefore, only a technical strategy, which produces consistently superior returns and lower volatility, can assuredly "beat" a buy and hold strategy in a meaningful way.

Poole (1967) was the first academic to apply technical signals to the foreign exchange markets. Analyzing nine different foreign exchange markets, Poole compared ten separate filter rules to a buy and hold strategy for each currency. Poole discovered that four out of the nine forex markets he studied generated an average annual rate of return of twenty-five percent, with

the best three each capturing an average annual rate of return of over forty-four percent, well over a buy and hold strategy for each currency, however Poole did not consider transaction costs in his research, which certainly would pull his returns closer to those exhibited by the buy and hold approach.

Van Horne and Parker (1967) expound on the work of Cootner's '62 paper by comparing the results of a buy and hold strategy for thirty widely held NYSE stocks against nine day trading strategies comprised of three different simple moving averages, each with three different bands. After considering commissions, all banded moving averages underperformed a simple buy and hold strategy. James (1968) applies the same technical trading strategy utilized by Cootner's '62 paper for a universe of over thirteen hundred CRSP stocks. James did not consider transaction costs or dividends in his research, but found that even without these considerations, Cootner's same approach could not consistently outperform a buy and hold strategy for any stock in the CRSP universe. Van Horner and Parker (1968) are the first to compare both simple as well as exponential moving averages for the same thirty NYSE stocks, over the same sample period as their '67 paper. Van Horner and Parker discovered that after transaction costs are considered, neither a simple nor exponential moving average could consistently outperform the benchmark across all securities considered. Some moving averages seem to outperform a buy and hold strategy for specific stocks and not others, thus no moving average, simple or exponential, with or without a band, was found to generate consistent outperformance against the benchmark for all of the securities considered in the study.

Jensen and Benington (1970) utilize the two relative strength indicators from Levy's '67 paper, applying the relative strength indicators as monthly long/short indicators across twenty-nine stock portfolios, all from the same universe of two hundred NYSE stocks. The authors

compare each portfolio's returns against a buy and hold benchmark of the stock universe, while simultaneously applying two percent transaction costs per round trip. After considering transaction costs, neither one of Levy's relative strength indicators was able to produce consistent excess returns. All stock portfolios performed worse than a simple buy and hold strategy of the stock universe. No dividends were considered by the authors, which perhaps would only serve to improve the results of the buy and hold strategy.

Stevenson and Bear (1970) utilized filter rules combined with stop loss orders based off the filter rules in order to day-trade July corn and soybean futures contracts. Each one way transaction costs fifty cents per bushel with the day trading results benchmarked against a buy and hold strategy of the same corn and soybean futures contracts. The authors discover that the five percent filter rule with a stop-loss order not only generated consistent excess returns above a buy and hold strategy, but also generated higher risk adjusted returns than the buy and hold strategy. Unfortunately, the authors never measured the statistical significance of their excess returns to let the reader know if combining filter rules with stop-loss orders does offer consistently higher risk adjusted returns over the buy and hold strategy.

Dryden (1970) compared one dozen filter rules to a series of separate equity benchmarks in the UK equity markets. For every individual stock Dryden day traded, that stock's day trading returns would be compared to a buy and hold benchmark of the same individual stock. Dryden also applied this comparison to a stock index, which his individual stocks composed. Dryden discovered that, in the UK equity markets, after considering transaction costs, all buy signals generated from the applied filter rules consistently beat a buy and hold strategy of the same security. Filter rules utilized to generate sell signals did not fair as well, producing volatility in excess of what a buy and hold strategy would produce, with worse average returns.

Levy (1971) found a brilliant way to objectively test a day trading strategy composed of technical signals derived from several price chart patterns against a buy and hold benchmark of over five hundred NYSE stocks. The patterns are: head and shoulders, double bottom/double top, triangles, channels, flags, pennants and the like, in Levy's own words. This paper was the first to objectively analyze the results derived from day trading individual stocks using price chart patterns, as no author before Levy had discovered a way to objectively test these patterns before. Levy concluded that after a two percent round trip commissions was considered, that no price chart pattern produced excess returns over the buy and hold benchmark of the stock universe that Levy considered.

Leuthold (1972) day traded thirty live cattle futures contracts over a five-year period utilizing six different filter rules. No benchmark was considered in this study, but Leuthold did consider the effects of real world transaction costs of thirty-six dollars per round trip. Remarkably, a three percent filter rule produced an annualized rate of return during the five-year period of 115.8%. However, because no benchmark was used to compare these results, it remains unclear if these results are due to the success of the filter rule, or merely luck.

Martell and Philippatos (1974) take the notion of the most successful filter rule among many and consider a means of optimizing that filter rule in a dynamic fashion. The authors compare different filter rules for the period $t-1$, taking the most successful filter rule for that period, and applying it for the period t , where each t is one day. The authors compare a day trading strategy that incorporates the adaptive filter rule against two buy and hold benchmarks, one for September wheat, the other for September soybean futures contracts. The authors discover that the dynamic filter rule only produced consistent excess returns above a buy and hold strategy for the September wheat futures contract. The dynamic filter rule however, when

compared in terms of risk-adjusted returns, was able to produce higher risk adjusted returns for both wheat and soybean futures contracts than a buy and hold strategy was able to.

Praetz (1975) considered twenty-four different filter rules, comparing a day-trading strategy for each rule to a buy and hold strategy consisting of Sydney wool futures contracts. The author notes that fourteen out of twenty-four different filter rules were able to produce excess returns above a buy and hold strategy, while the other ten severely underperformed the benchmark. Thus, the author concluded that, at least in the Sydney wool market, that filter rules do not consistently beat a buy and hold strategy over the eight-year period that the author analyzed. The author however fails to indicate that the majority of filter rules did consistently outperform a buy and hold strategy. Even if all of the applied filter rules failed to outperform the benchmark, most did. Therefore, one could conclude that certain filter rules are better than others at capturing excess returns.

Martell (1976) takes his earlier work and moves one step further. The adaptive filter rule is further optimized in that the best filter is chosen from not only the most profitable filter from the period $t-1$, but also from period $t-2$, $t-3$, etc. In this way, Martell discovers that his new adaptive filter rule is more successful than his previous model. Again Martell compares his adaptive filter rule to a buy and hold benchmark of both September wheat and September soybean futures contracts. This time, the author notes how this new adaptive filter rule outperformed his old rule eighty percent of the time, beating both benchmarks in terms of both higher average returns and higher risk adjusted return.

Akemann and Keller (1977) compared Levy's relative strength indicator as a weekly buy/sell indicator for the individual stocks in the S&P 500, against a buy and hold strategy of the entire S&P 500 index. The authors considered a two percent round trip transaction cost without

adding the effects of dividends for either strategy. The weekly trading strategy is simple, buy the stock decile with the highest return during a thirteen-week period, and sell this group after fifty-two weeks. The authors note how, after adjusting for the cost of commissions, the mean excess rate of return considered against the benchmark index is 14.6%. However, the authors do state that the variance in excess returns was much higher than the benchmark, preventing them from concluding that their strategy consistently outperformed the benchmark in terms of pure skill.

Logue and Sweeney (1977) compare fourteen filter rules in the foreign exchange market for French francs. The authors compare a day trading strategy consisting of different filter rules to a buy and hold benchmark of the French franc, also considering a one way transaction cost of six basis points per transaction. The authors discover that thirteen out of fourteen filter rules outperformed the benchmark after considering transaction costs over a four-year period. The authors also compare their results to a benchmark of French government securities, discovering that only four filter rules failed to beat this benchmark in terms of higher mean return.

Cornell and Dietrich (1978) analyze thirteen filter rules and three simple moving averages with different bands ranging from one tenth to two percent about the average for six different foreign exchange markets: the mark, the pound, the yen, the loon, the Swiss franc, and the Dutch guilder over a two year period. The best rule for each currency was able to beat a buy and hold strategy per each currency, ranging from an annualized average of one percent excess return to ten percent excess return. Logue, Sweeney, and Willett (1978) compare eleven filter rules for seven different forex markets: mark, pound, lira, yen, French franc, Swiss franc, and Dutch guilder over a three-year period. The authors conclude that for every currency, one of the filters was able to generate excess returns over a buy and hold strategy, without considering transaction costs, ranging from 9.3% to 32.9%. Filter rules, moving averages, and relative

strength indicators would continue to be the most successful and popular of all individual technical signals considered by academics until linear regression models, popularized by Fama and Arnott, began to dominate the literature towards the end of the twentieth and into the twenty-first century.

Arnott (1979) developed a linear regression model to analyze beta adjusted relative strength for one thousand stocks, five hundred from the NYSE and all the individual stocks in the S&P 500 on a weekly basis over a nine-year period. Arnott would be the first serious academic to utilize a linear regression model in his analysis of the equity markets. Arnott concluded that the correlation between beta-adjusted relative strength and subsequent period weekly returns was highly negative, indicating that beta-adjusted relative strength could serve as a contrarian indicator for the stock market. Arnott did not compare his results to any benchmark; he merely investigated the correlations between future returns and his indicator of choice.

Dale and Workman (1980) are the first to apply a form of technical analysis as academics to the US T-bill futures market. The authors compared eleven different moving averages over a two year period, while also considering a \$60 round trip transaction cost, no benchmark was considered in this study. The authors noted that the best moving average was able to capture positive average returns, though the large variance in these returns indicated that the positive results were most likely due to chance. Also, since ten out of eleven signals failed to generate positive average returns, the success of one signal is most likely due to pure luck.

Bohan (1981) utilizes a weekly trading strategy based off of the relative strength indicator with the most success thus far compared to his academic peers in deriving economic profit out of the equity markets. Bohan buys the quintile, twenty percent, of stocks in the S&P 500, which have the highest relative strength, while selling the quintile of stocks in the index that

have the lowest relative strength. Bohan analyzes his strategy over an eleven-year sample period with two percent annual costs against a buy and hold benchmark of the entire S&P 500 index. Bohan discovered that the top quintile of stocks with the highest relative strength outperformed the market by an average annualized amount of 7.6%, while the bottom quintile underperformed the market by an average annualized amount of 8.0%. Therefore by buying the stocks with the highest relative strength and selling the stocks with the lowest relative strength, and rebalancing on a weekly basis, Bohan was able to demonstrate that it is possible to capture consistently positive excess returns in the US equity markets.

Solt and Swanson (1981) combine both filter rules with simple moving averages in an attempt to create a more accurate buy/sell signal. The authors trade both gold and silver futures over a nine-year period on a weekly basis, considering one percent transaction costs as well as half a percent annual fees. Finally, the authors compare their results against a buy and hold benchmark of both physical commodities. Interestingly, only the ten percent filter rule was able to generate consistent excess returns over a buy and hold strategy, and only for gold, not silver. The simple moving average filter rule combination did not outperform either benchmark. While these results seem to indicate that combining signals is perhaps of little value, it is important to note that the combined approach applied by Solt and Swanson (1981) differs from the combined signal approach applied by this research paper. Solt and Swanson placed filters based off of the location of their moving averages. While in this paper, the idea is to utilize the signals in concert with one another, each signal contributing a single vote to help determine a long/short position.

Peterson and Leuthold (1982) successfully capture consistent economic profit utilizing twenty filter rules in order to day trade CME hog futures contracts. The authors compare their results to an expectation of zero mean profit, without considering the effect of transaction costs.

However, the authors note that all filters were able to capture “considerable mean gross profits”. Also, the authors discovered that larger filters captured larger mean profits and larger variance of profits. Interestingly, the work of Dooley and Shafer (1983) says the exact opposite. Dooley and Shafer tested filter rules on nine foreign currencies in the New York forex market, without considering either commissions or a benchmark of any kind. The authors noted that smaller filters produced larger mean profits, while larger filters yielded consistent losses.

Brush and Boles (1983) expand on the work of Bohan’s ’81 paper, utilizing a relative strength indicator as a means of capturing economic profit from the S&P 500 index. Brush and Boles utilized a relative strength indicator in order to form equal weighted deciles of the individual stocks in the S&P 500 index, buying the top decile, and selling the bottom decile, and rebalancing monthly. Transaction costs are flat at two percent per round trip. The authors compare their results to the S&P 500 index including dividends. Brush and Boles surpass the earlier work of Bohan by capturing excess return, even after considering the effects of dividends against the S&P 500 index. Over a three-year period, the authors were able to capture an annualized average excess rate of return of 9.3% against the S&P 500, even after considering dividends. Many hedge fund and portfolio managers would later be inspired by this research, utilizing it to form the bread and butter of their market neutral trading strategies.

Irwin and Uhrig (1984) day traded eight different agriculturally based futures contracts: corn, cocoa, soybeans, wheat, sugar, copper, live cattle, and live hogs over an eighteen-year period. Utilizing Donchian inspired channels, simple moving averages, and momentum oscillators, the authors evaluate their results against a zero mean profit benchmark with commissions implied, though not explicitly stated. The authors found that across all contracts, all three types of technical signals were able to capture positive mean profits.

Neftci and Policano (1984) day trade copper, gold, soybeans, and T-bills on a daily basis utilizing three simple moving averages, along with a unique trend-line method. The trend-line, or slope method, as its alternatively called, looks for timing opportunities based on the asset's price mean reverting back to the trend-line once a significant enough deviation has occurred. The authors consider neither a benchmark with which to compare their results, nor do they consider any transaction costs. Uniquely, these authors are some of the first to employ a linear regression model in academic research centered on technical analysis. The buy/sell signals derived from the moving averages and the trend-line method were transformed into dummy variables that were then plugged into the regression equation. As dummy variables, the technical signals proved to all be statistically significant using F-tests. Also, the regression was able to extract consistent positive mean profits from gold, soybean, and T-bill futures contracts, while the model was unsuccessful at extracting positive mean profit by trading copper futures.

Authors Tomek and Querin (1984) develop a unique test for determining the utility of technical analysis. The authors create three random price series based off of corn prices, one with average volatility, the second with larger volatility, and the third with positive drift. The authors then test two MACD technical signals, one 3/10 signal, the other a 10/40 signal on each random price series. MACD signals are a form of moving average indicator that uses two moving averages, for example a three-day and a ten-day moving average. When the shorter moving average crosses below the longer moving average, that indicates a sell signal, when the shorter moving average crosses above the longer moving average that indicates a buy signal. The authors conclude that while technical signals may offer positive mean returns some of the time, over a long enough sample period any technical signal should not be expected to generate positive mean profits.

Bird (1985) day trades copper, lean, tin, and zinc from the LME over a ten year period using twenty-five filter rules, only utilizing the rules' buy signals, never making a short transaction. Bird evaluates his performance against a buy and hold strategy of each metal separately, while also considering one percent round trip transaction costs. Concluding that seventeen out of twenty-five filter rules generate average returns in excess of a buy and hold strategy, even when considering transaction costs. What is most interesting about the author's strategy is his refusal to take short positions. Obviously market prices move about randomly, but if one only looks at a long-term price chart it becomes rather self evident, that, while prices may move randomly, certain markets do in fact exhibit positive drift. Due to this positive drift, most of the time the market will move up, Bird obviously was well aware of this and developed a strategy that employed positive drift instinctively, by only taking long positions.

Brush (1986) continued where Bohan (1981) and Brush and Boles (1983) left off, attempting to improve the results of the relative strength indicator against the S&P 500 index. Brush, unlike his previous work, utilizes the equal-weight version of the S&P 500 index as his benchmark, due to the fact that his portfolio is an equal weight portfolio, therefore he reasons that his benchmark should also be equally weighted. Brush applies a one percent round trip transaction cost to his results, this time however, Brush compares eight different relative strength models. His most successful model involves buying two deciles, one of S&P 500 stocks with the highest relative strength, and one decile consisting of stocks with the highest value. Highest value stocks are defined as those stocks with the highest book to market ratio. Brush concludes that an equally weighted portfolio consisting of two components, one decile of stocks with the highest relative strength and the other decile of stocks with the highest value yields an annualized average return of 5% in excess of the equally weighted S&P 500. Remarkably, Brush

noticed that both value, as a fundamental indicator, and relative strength as a technical indicator, tend to generate returns that offset one another. Therefore a portfolio that combines both strategies does better than either one separately.

Sweeney (1986) uses various filter rules on nine separate currencies in the forex markets. Much like Bird, Sweeney only takes long positions as a rule of his analysis. Sweeney compares each currency's day trading results to a buy and hold benchmark of that particular currency. Seven filter rules are compared with round trip transaction costs consisting of $1/8^{\text{th}}$ of one percent of the total asset value invested in any currency at any given time. Sweeney discovers that for six separate currencies, he is able to capture excess returns by using the smaller filter rules. Sweeney, interestingly enough is also one of the first authors to test the statistical significance of his excess returns, proving that technical analysis in at least the forex markets, is not caused by luck but rather is due to the alpha generating ability of Sweeney's signal(s)/strategy.

Taylor (1986) utilizes a statistically based price-trend model, which focuses on predicting a security's short term price trend and then capitalizing on riding that trend. Taylor's model decides whether the future trend will be flat, positively, or negatively sloped, by optimizing a maximum likelihood indicator using a genetic algorithm developed by Holland (1975). Taylor tested his model by day trading three agricultural commodity futures contracts: cocoa, coffee, and sugar, and three foreign currency futures contracts: British pound sterling, German marks, and Swiss francs. Taylor applies a one percent round trip transaction cost for day trading agricultural commodity futures contracts and a one-fifth of one percent transaction cost for day trading currency futures contracts. Taylor also compares his day trading results to a buy and hold strategy for every agricultural commodity he trades, while using a country's average bank deposit rate as a benchmark for each currency he trades. Taylor's model was able to capture an

annualized average return of 27% in excess of a buy and hold strategy for sugar futures. Taylor was unable to capture excess returns against a buy and hold strategy for either cocoa or coffee futures. Taylor was unable to generate returns in excess of any of the three bank deposit rate benchmarks, except in the last year of his analysis, when his model generated an annualized average return of 7% in excess of each bank deposit rate for each currency he traded. Taylor was the first to employ a genetic algorithm to optimize a model's predictive power in order to more accurately forecast the next day's price trend. Ahead of his time, Taylor's algorithmic based trading foreshadowed how US equity markets operate today, dominated by algorithmic based high speed trading done by supercomputers.

Thompson and Waller (1987) utilize several filter rules to trade both cocoa and coffee futures on a six-week basis, without comparing their results to a benchmark strategy. The fatal flaw in most cases where filter rules are applied is the number of transactions necessary to produce a profit overrides any profit that the filter rules is usually able to capture. While filter rules are able to capture average profits that are statistically significantly greater than zero. The authors discover that the average profits per each commodity are lower than real world transaction costs.

Lukac, Brorsen, and Irwin (1988) test numerous individual technical signals, along with a combined signal on numerous agricultural, metal, currency, and interest rate futures. The authors test: three channels, three moving averages, three momentum oscillators, two trailing stops, and a combination of the aforementioned signals. The authors test their strategy against a zero mean profit benchmark with a flat round trip transaction cost of one hundred dollars. Four of the trading strategies tested generated statistically significant returns above the benchmark. These same four strategies also produced returns that are more risk efficient than their respective buy

and hold strategies. Meaning, that some technical trading strategies are capable of generating not only economic profit, but returns with higher risk efficiency.

Lukac and Brorsen (1989) test various trading strategies: re-optimization, random, and fixed parameter strategies using both channel signals and directionally based signals on various agricultural, metal, currency, and interest rate futures. The strategies are tested against a buy and hold strategy for each asset, with round trip transaction costs of one hundred dollars. Both technical signals offer statistically significant returns in excess of their buy and hold counterparts. However, different optimization strategies, as well as the random strategy offer no substantial improvement against a buy and hold strategy, thus because fixed parameters captured the only consistent and statistically significant excess returns, the authors conclude that re-optimizing parameters offers no real value in capturing economic profit.

Sweeney and Surajaras (1989) test three technical trading strategies by day trading two portfolios of currency futures contracts: one equally weighted, the other variable weighted over a six-year period. The technical signals the authors employ are: filter rules, single simple moving averages, and double simple moving averages. The authors also tested various rebalancing schemes aimed at optimizing trading profits based off risk efficiency. Of all the signals tested, the single simple moving average performed best across both value and equally weighted portfolios, with the variable weighted portfolio yielding the most economic profit. While both portfolio balances managed to beat a buy and hold strategy of the basket currencies by utilizing a single simple moving average, no rebalancing optimization technique proved useful in improving either profits or risk efficiency.

Taylor and Tari (1989) again test Taylor's price-trend model on several currency and agriculturally based futures contracts: British pound, German mark, Swiss franc, cocoa, coffee,

and sugar. The strategy is tested against a buy and hold benchmark of each asset, with round trip transaction costs of one percent for commodity futures, and one-fifth of one percent for currency futures. Over the ten year sample period that the price-trend model was tested upon, the model only generated economic profit above a buy and hold strategy for three out of six contracts: the German mark, cocoa, and sugar contracts. The authors do not test whether the economic profits they captured are statistically significant. However, because the model was only successful for half of the contracts considered, it is unlikely that Taylor's price-trend model in its current form has persistent forecasting abilities. In a few years however, Taylor would revise his model, making its success comparable to the success of other much simpler technical signals: filter rules and moving averages.

Lukac and Brorsen (1990) are the first to consider the utility of volatility as a potential technical trading signal. The authors test a variety of technical signals by day-trading thirty different futures contracts, consisting of: agricultural commodities, precious metals, oils, currencies, interest rate futures, and S&P 500 futures over a ten year period. The success of trading each futures contract is compared to a zero mean profit benchmark with one hundred dollar round trip transaction costs. The various technical signals that the authors test includes: channels, simple moving averages, momentum oscillators, trailing stops, point and figure charts, a counter-trend model, a volatility based model, and finally a combination of all the above signals.

The authors utilize the well-known fact that historical volatility levels persist during the short term, while reverting to the mean over the long run. Assets with relatively higher volatility than their historical mean tend to underperform their historical mean rate of return, while assets with relatively lower volatility than their historical mean tend to outperform their historical mean

return. The authors use historical volatility as a buy/sell indicator, buying an asset with relatively low historical volatility, while selling an asset with relatively high historical volatility. Once volatility passes its historical average, the position is reversed. The authors test historical periods from one day to one year, in order to find the optimal time period for using historical volatility as a technical signal. Out of the twenty-three technical signals tested, only three generated negative mean profits after considering transaction costs, the rest of the signals generated positive mean returns, with seven out of twenty-three signals generating an annualized average rate of return greater than ten percent after transaction costs. The authors conclude that the short-term disequilibrium model more accurately describes daily futures prices than the random walk model.

Taylor (1992) tests a revision of his statistical price-trend model using a ten-year sample period, with a five-year in sample period and five-year out of sample period, in order to optimize his price-trend model. Taylor tests his model by day trading four currencies: German mark, British pound, Japanese yen, and Swiss franc. Taylor compares two revised versions of his original statistical price-trend model along with a filter rule, channel, and simple moving average. Taylor compares his results against a buy and hold strategy of each currency, considering a transaction cost of twenty basis points per round trip. Taylor's revisions of his original price-trend model produce statistically significant returns in excess of the buy and hold strategy for each currency considered. Each of the other trading signals also produce statistically significant returns in excess of a buy and hold strategy, again for all currencies considered. Taylor's work illustrated concrete statistical evidence against the random walk model as the best explanation for how forex prices move.

Farrell and Olszewski (1993) day trade S&P 500 futures contracts over an eight-year period. The authors test a nonlinear statistical model based on the ARMA (1,1) model, along side

one channel and two different volatility models. The authors consider a total transaction cost of two and a half basis points per round trip. The authors compare each technical signal against a buy and hold strategy of the nearest S&P 500 futures contract. The statistical model that the authors test is in fact a combination of two technical models: one is an autoregressive model, the other a moving average.

The autoregressive model is a time series model that describes a random process with random shocks. The moving average model is the summation of a historical mean rate of return along with a random variable. The two models combined form a nonlinear random walk model. The authors other signals: one channel signal and two volatility signals, are based off of the works of other authors, Donchian is the author who was the first to utilize price channels, while Lukac and Brorsen were the first to utilize volatility as a trading signal. The authors revise the historical volatility model by making two separate models. One model compares daily historical volatility to an in sample optimized historical mean; the other model compares weekly historical volatility to an in sample optimized mean historical mean. The authors are able to capture statistically insignificant returns in excess of a buy and hold strategy by utilizing a trading strategy that incorporates the ARMA (1,1) model. However, the other technical signals: one channel signal, and two volatility signals, all offer statistically significant returns in excess of the buy and hold strategy.

Previous authors were only able to capture statistically significant excess returns by utilizing either some sort of technical signal(s) or some sort of price-trend model; no author has ever consistently captured excess returns with the help of a random walk model. Previous authors also dismiss the claim that the random walk model is the best descriptor for how the futures market operates: Lukac and Brorsen (1990) and Taylor (1992). Farrell and Olszewski

conclude that since their ARMA (1,1) based trading strategy does not offer consistent excess returns, while other technical signals do, that the random walk model is not the best descriptor for how the S&P 500 futures market operates.

Silber (1994) day trades twelve different futures markets, consisting of: foreign currencies, precious metals, oils, interest rates, and S&P 500 contracts. The author analyzes the returns captured by several simple moving averages with varying lengths from one day to two hundred days. The author considers a round trip transaction cost equivalent to the particular market's bid-ask spread, between one and two ticks. Silber compares his day trading results against a buy and hold trading strategy. Silber concludes that after transaction costs, his strategy generated an annualized average return in excess of a buy and hold strategy for nine out of the twelve different futures markets in which he day traded. Silber does not test for statistical significance, but does compare the Sharpe Ratios of his results against the Sharpe Ratios of the buy and hold benchmarks, discovering that his day trading strategy produces more risk efficient returns than a buy and hold strategy does, again only for nine out of twelve markets. Silber discovered that the most profitable futures market is the forex market, concluding that technical analysis is most effective in the forex markets because of central bank intervention imbuing the forex markets with aspects of non-randomness, which makes market direction somewhat predictable.

Taylor (1994) day trades four currency futures contracts: British pound, German mark, Japanese yen, and Swiss franc. The author analyzes several price channels, testing the specific price channel that produces optimal in sample results. Taylor compares his day trading results against a zero mean profit benchmark, along with the consideration of transaction costs, equivalent to twenty basis points per round trip. Taylor discovered that the optimal price channel

signal correctly predicted the daily direction of each currency futures contract about sixty percent of the time in the out of sample period. Taylor also discovered that the optimal price channel generated an annualized average rate of return of 6.9% after transaction costs, these results are statistically significant. Taylor's research provides credibility to technical analysis as a means of predicting price movements. The fact that technical signals have the ability to capture statistically significant and persistent excess returns itself contradicts the notion that prices walk randomly through time.

Menkhoff and Schlumberger (1995) day trade three exchange rate futures contracts: German mark/US dollar, German mark/Japanese yen, and the German mark/British pound, in order to test various optimized technical signals: momentum oscillators and simple moving averages, against a buy and hold strategy of each exchange rate. Results of both strategies are compared after transaction costs are considered, which varies between eight to thirty basis points per round trip. The authors analyze their results over a ten-year total sample period, with a five-year in sample period and a five-year out of sample period. After transaction costs, the optimal trading rules derived from the in sample period outperformed their buy and hold benchmark strategies in terms of both higher average return and higher risk efficiency. The authors did not test for statistical significance, and claim that the optimal trading rules' effectiveness deteriorated towards the end of their out of sample period. Therefore the reliability of the authors' strategy is questionable in the long run.

Lee and Mathur (1996a) day trade six European currency futures contracts over a five-year period. The authors test a double moving average strategy, a combined signal strategy of sorts: one short term moving average, from one day to nine days, the second a long term moving average, from ten to thirty days, in five day increments. When both moving averages indicate the

same directional sign, the signal, either buy/sell, is said to be confirmed, and therefore a much more reliable technical signal. The authors compare their optimized strategy against a zero mean profit benchmark, with transaction costs equivalent to ten basis points per round trip. After transaction costs, the results of the authors' trading strategy indicate that no statistical significance is found either in or out of sample period for any of the aforementioned trading rules. In fact, across all currencies considered, in the out of sample period, the average annualized rate of return of the authors' day trading strategy is only marginally positive. It seems that for every paper that finds refutable evidence against the random walk model, there is another paper that supports the random walk model, finding no evidence that technical analysis generates consistent excess returns.

Lee and Mathur (1996b) continue to revise their original technical trading strategy, analyzing even more double moving average combinations to find the optimal simple moving average pair, along with an optimal price channel. Similar to their previous paper, the authors consider a round trip transaction cost of ten basis points and a zero mean profit benchmark. This time around, the authors test their strategy on ten futures contracts, all of them cross rate currencies. Most of the double moving average technical signals captured statistically insignificant yet positive annualized mean returns. Only the German mark/ Italian lira cross rate provided both the optimal double moving average and the optimal price channel with statistically significant positive annualized mean returns out of sample. Therefore, because the authors only found statistical significance out of sample for one out of ten cross rate futures contracts, there is very little evidence that either optimal trading signal refutes the random walk model.

Szakmary and Mathur (1997) day trade five foreign currency futures contracts: German marks, Japanese yen, Swiss francs, British pounds, and the Canadian dollar, in order to

test the optimal double simple moving average combination. The day trading strategy is compared to a zero mean profit benchmark with a round trip transaction cost of ten basis points. The authors discover that during the out of sample period, the optimal double moving average combination technical trading rule captures positive and statistically significant annualized mean returns against the benchmark for all currency futures contracts considered except the Canadian dollar. The authors conclude that central bank intervention in the forex markets is the source of their persistent profitability. Giving credence to the theory that central bank/government intervention imbues specific markets with aspects of non-randomness, making these markets directionally predictable.

Goodacre, Boshier, and Dove (1999) day trade 254 out of 350 stocks in the FTSE 350 index, along with 64 options in the UK options market in order to test the CRISMA strategy. The authors compare their day trading strategy to a buy and hold strategy of the FTSE 350 index, while also considering transaction costs at two percent per round trip; no test for statistical significance is performed. CRISMA combines three technical signals into one: Cumulative Volume Index, Relative Strength Indicator, and Moving Average. The authors test an optimized CRISMA during their out of sample period by optimizing the components of the strategy over a two hundred day in sample period. The Cumulative Volume Index adds all shares of a security that are bought and subtracts all shares of a security that are sold over a pre-specified timeframe. This allows the analyst to gauge the most likely short-term direction of a security. In fact, all three technical signals that CRISMA incorporates are momentum indicators in one form or another; the relative strength indicator compares a security's most recent performance to that of the security's average performance during the most recent financial quarter, in order to determine if a security has relative strength or relative weakness. Moving averages also compare a

security's most recent performance to a historical average to gauge whether a security has positive or negative momentum. When technical signals are combined the result is hopefully a stronger signal, more so than if the same signals were utilized independently. The authors discover that CRISMA, even after optimizing the component trading rules, captures mixed results. Day trading some stocks generated positive annualized mean returns in excess of the buy and hold benchmark, some stocks generated negative annualized excess mean returns, when compared to the buy and hold benchmark, after transaction costs were considered. The CRISMA strategy did manage to generate an annualized mean rate of return of 10.2%, after transaction costs, by day trading option contracts, however the strategy was unable to correctly predict the daily directional sign(s) with any significant accuracy, thus CRISMA's utility in either the equity or options market is perhaps no different than any other technical signal one might consider. Further applications of the same and other combined technical signal trading strategies also offer mixed results, some combined strategies outperform their respective benchmark, others underperform their respective benchmark, even when a strategy offers statistically significant excess returns, it is difficult to determine if said returns are captured because of the strategy's inherent skill, or is the market at that time being influenced in a way that makes it behave somewhat predictably.

Kwam, Lam, So, and Yu (2000) day trade Hang Seng Index futures contracts in order to test their statistical price-trend model. The authors consider a one-way transaction cost of fifty basis points and compare their day trading strategy to a buy and hold strategy of the underlying Hang Seng Index. The authors utilize a nine-year in sample period in order to optimize their model's parameters, testing their model in earnest on a nine-year out of sample period. The authors discover that their statistical price trend model underperformed a buy and hold strategy

when the underlying stock index was bullish, however when the underlying index did not trend significantly in either up or down direction, their model outperformed the benchmark. After considering for transaction costs, and analyzing the whole out of sample period, the authors conclude that their statistical price-trend model underperformed a buy and hold strategy on average of 3.4% per year. The model's inability to accurately identify and follow the bullish trend of the underlying stock index is what caused the authors strategy to underperform the index.

Maillet and Michel (2000) day trade twelve exchange rate futures contracts, utilizing combinations that include: US dollar, German mark, Japanese yen, British pound, and French francs. The authors test a double simple moving average trading strategy that utilizes the optimal parameters derived from the best results discovered in the in sample period. The authors compare their day trading strategy to a zero mean profit benchmark, without considering transaction costs. The authors find that the optimized double simple moving average day trading strategy produces statistically significant annualized returns in excess of a zero mean profit for all exchange rate futures contracts except the mark/franc. The authors retest their results via a Bootstrap method, concluding that after bootstrapping, statistically significant excess returns were captured for eight out of the twelve exchange rate futures contracts. These results do not yield conclusive evidence that the exchange rate futures market is predictable because the authors fail to consider transaction costs.

Taylor (2000) day trades numerous individual stocks and several stock index futures contracts: The Financial Times All Share Index futures contracts, the UK 12-Share Index futures contracts, 12 UK stocks, FTSE 100 stock index futures contracts, DJIA index futures contracts, and S&P 500 index futures contracts, in order to test an optimized double simple moving average day trading strategy. Taylor compares his strategy to a buy and hold strategy, adding a

transaction cost of thirty-five basis points per transaction. Taylor optimizes his combined signals' parameters over an in sample period that ranges from 1897-1968, testing his strategy in earnest during an out of sample period that extends from 1969-1992. Taylor discovered that for all securities considered, day trading the FTSE 100 and S&P 500 produced statistically insignificant returns in excess of a buy and hold strategy, while day trading all other securities, except the DJIA, produced statistically significant returns in excess of a buy and hold strategy. Taylor's worst results were realized from day trading the DJIA, which yielded, after transaction costs, break even profits, significantly underperforming a buy and hold strategy. Any technical signal that is successful in capturing statistically significant excess returns when utilized to day trade one security, will most often times fail to produce the same results when utilized on another security. It is this inconsistency in results that prevents technical analysts from refuting the random walk model.

Goodacre and Kohn-Spreyer (2001) day trade a random sample of three hundred twenty-two stocks from the S&P 500 index in order to test an optimized CRISMA based trading strategy. The authors compare their day trading results against a buy and hold strategy of the entire S&P 500 index, while also considering a commission of one percent per round trip. The authors optimize every parameter within CRISMA over a two hundred day in sample period, utilizing the parameters that provide CRISMA with the best results from that sample period. Once CRISMA is optimized, the authors test their strategy in earnest during an eight-year out of sample period. After transaction costs, the authors discover that their strategy does not produce an annualized mean rate of return in excess of a buy and hold strategy, rather the authors' strategy underperforms the S&P 500 index by an average of 2.1% per year. Instead of comparing a day trading strategy consisting of the whole stock index against a buy and hold strategy of the

same index, the authors day trade a random sample of stocks. If the random sample of stocks, happens to underperform/outperform the entire index, the failure/success of the day trading strategy is perceived to be caused by the technical signal, while it may be due to the fact that the authors were comparing apples to oranges.

Lee, Gleason, and Mathur (2001) day trade thirteen Latin American spot rate currency contracts in order to test an optimized double simple moving average combined signal, along with an optimized price channel. The authors compare their day trading strategy to a zero mean profit benchmark, with trading costs equivalent to ten basis points per round trip. The authors optimize their parameters over a one-year in sample period, testing the two optimized signals over a seven year out of sample period. After transaction costs, the authors discover that by only taking long positions, they are able to generate statistically significant positive returns in excess of a zero mean profit benchmark for five/four currencies considered, by using the optimized double simple moving average indicator/optimized price channel indicator. Also, after transaction costs, the authors capture statistically insignificant returns in excess of the zero mean profit benchmark, for all other currencies considered. Therefore, because neither optimized trading rule was able to capture statistically significant results across all currencies considered, the predictive power of either optimized trading rule is doubtful.

The variable success of simple moving averages and filter rules makes these indicators the most extensively tested technical signals in the academic literature. The following research regarding technical analysis focuses solely on variations of three technical trading signals: simple moving averages, filter rules, and trading range break out rules, itself a variant of the filter rule. The inspiration for Camillo Lento's Combined Technical Signal Approach is in part due to the robust success of the three aforementioned signals, as well as the success of various combined

technical signals, which is also well documented by the following authors.

Brock, Lakonishok, & LeBaron (1992), Levich & Thomas (1993), Bessembinder & Chan (1995), Hudson, Dempsey, & Keasey (1996), and Kho (1996) day trade: the DJIA, five currency futures, six Asian stock indices, the U.K. FT 30 stock index, and four currency futures respectively, with Kho trading currency futures on a weekly basis. All authors, with the exception of Levich and Thomas, compare several double moving averages combined with various percentage bands and trading range break out rules to a buy and hold strategy. Levich and Thomas compare the returns produced from several double moving averages and filter rules to a buy and hold strategy. Brock et al. and Kho are the only authors who do not consider the effects of transaction costs. Levich and Thomas consider a four basis point one way transaction cost, Bessembinder and Chan consider various transaction costs, from fifty basis points to two hundred basis points, and Hudson et al. consider a round trip transaction cost of one hundred basis points.

Brock et al. discovered that buy signals produced from their technical trading strategy produced an annualized average rate of return in excess of a buy and hold strategy of five percent after transaction costs, while sell signals consistently produced negative excess returns, no measure of statistical significance is performed. Levich and Thomas discover that for all filter rules and moving averages considered, twenty-five out of the thirty technical signals produced statistically significant returns in excess of a buy and hold strategy, after transaction costs considered. Bessembinder and Chan, discover that U.S. based technical signals have predictive power in the Asian stock index markets. Across six stock indices, the authors captured, after transaction costs, between 12.2% and 21.2% in annualized returns. The authors also discover that by applying a daily round trip transaction cost of 1.57%, that their day trading strategy breaks

even with a buy and hold strategy, however the authors do not test for statistical significance. Hudson et al. after the application of transaction costs, reach the same conclusion as Brock et al., that positive excess returns are produced from buy signals, while negative excess returns are produced from sell signals, Hudson et al. do not test for statistical significance. Finally, Kho discovered that the moving average rules that he tested produced an annualized average rate of return of ten percent, after transaction costs considered. Kho also found that his weekly trading results were statistically insignificant when compared to a conditional form of the CAPM. In summary, all authors are able to beat a naïve buy and hold strategy when only buy signals are utilized, though the level of significance per author varies substantially.

Raj & Thurston (1996), Mills (1997), Bessembinder & Chan (1998), Ito (1999), LeBaron (1999) all day trade equity indices: Hang Seng and Hong Kong stock indices, U.K. FT 30, DJIA, the Toronto stock index, the Mexico stock index, the Taiwan stock index, the Indonesia stock index, and the Nikkei index, with the exception of LeBaron, who day trades currency futures contracts. All authors compare the same trading rules, moving averages and trading range break out rules, applied in the Brock et al. (1992) paper, against a buy and hold strategy. Raj and Thurston, and Mills are the only authors who do not consider the effects of transaction costs. Bessembinder and Chan consider a cost of commissions of forty basis points per one way, Ito considers a cost of commissions of eleven basis points per one way, LeBaron considers a round trip transaction cost of sixty-five basis points.

Raj and Thurston discover that statistically significant returns are generated from buy signals produced from all moving average rules and trading range break out rules. Trading range break out rules produce substantially higher returns than a buy and hold strategy, averaging six hundred twenty percent per year, against thirty-nine percent for the buy and hold strategy,

although neither transaction costs, nor volatility of returns are taken into account, thus the statistical significance of these phenomenal results is unknown. Mills compares his day trading strategy's returns against numerous bootstrapped simulations of the original return series. Mills discovers that the excess returns he generated are statistically insignificantly greater than returns produced by a buy and hold strategy, even though Mills does not adjust for transaction costs. Bessembinder and Chan compare their day trading results against a buy and hold strategy of the DJIA, including both transaction costs and dividend payments. The authors discover that their day trading strategy produces higher average returns than a buy and hold strategy, even after considering both commissions and dividends, however, no mention of the strategy's statistical significance is mentioned. Ito discovers that after transaction costs, trading rule profits are greater in all cases, besides the DJIA, than a buy and hold strategy. Ito concludes that generally the excess returns typically associated with technical trading strategies are fair compensation for higher risks that he associates with technical trading. Lastly, LeBaron discovered that utilizing a moving average trading strategy produced statistically significant profits; even after transaction costs were considered. LeBaron concluded that statistical significance was caused by Federal Reserve intervention, stating that whenever the Federal Reserve actively intervened in the currency markets, higher than average profits could be expected, while periods where the Federal Reserve did not actively intervene in the currency markets, coincided with lower than average technical trading profits.

Ratner & Leal (1999), Coutts & Cheung (2000), Parisi & Vasquez (2000), Raj (2000), and Gunasekarage & Power (2001) day trade: ten Asian and Latin American stock indices, the Hang Seng and Hong Kong stock indices, the Santiago stock index, Japanese yen and German mark currency futures contracts, and the Bombay, Colombo, Dhaka, and Karachi stock indices

respectively. All aforementioned authors compare their day trading results to a buy and hold strategy. Also, all aforementioned authors, besides Ratner and Leal, and Raj, employ the same technical trading strategy applied by Brock et al. (1992). All authors, besides Coutts and Cheung, and Gunasekarage and Power make adjustments for the effect of transaction costs. Ratner and Leal consider a one-way transaction cost of one hundred basis points, Parisi and Vasquez apply the same one hundred-basis one-way transaction cost, and lastly, Raj applies a four basis point transaction cost per one-way trip.

Ratner and Leal discovered that out of ten equity indices and ten variations of the simple moving average, only twenty-one out of the one hundred total scenarios produced statistically significant returns in excess of a buy and hold strategy, after transaction costs were considered. Coutts and Cheung discovered that positive statistically significant excess returns were captured from buy signals produced from the trading range break out rule, while negative statistically significant excess returns were captured from sell signals produced by the trading range break out rule, no transaction costs are considered by the authors. Parisi and Vasquez discover that various moving average rules capture statistically significant and positive excess returns, even after considering the effect of transaction costs. Raj concludes that only one trading rule, a double simple moving average utilizing two days and two hundred days, captured statistically significant positive excess returns, after transaction costs were considered. Finally, Gunasekarage and Power discover that buy signals produced from various moving average trading rules generated statistically significant positive excess returns after transaction costs when compared to a buy and hold strategy, while sell signals produced from moving average trading rules generated statistically significant negative excess returns after transaction costs when compared to a buy and hold strategy. In review, all authors claim that buy signals produced

from moving averages and trading range break out rules have the potential to produce positive statistically significant returns in excess of a buy and hold strategy, while also claiming that sell signals have potential as a contrarian indicator. Since statistically significant negative excess returns are generated from sell signals, the authors infer that by consistently betting against the sell signal, they could potentially capture positive statistically significant excess returns.

Lee, Pan, & Liu (2001), Martin (2001), Skouras (2001), and Olson (2004) all day trade currency exchange rates, except in the case of Skouras, who day trades the DJIA index, in order to test various moving average technical trading strategies. The authors either test the double moving average trading strategy, or the strategy that incorporates a percentage band about the moving average. Lee et al. compare their results against a zero mean profit, while the other authors compare their day trading strategies to a buy and hold benchmark. All authors consider the effect of transaction costs: Lee et al. and Olson both apply a ten basis point round-trip transaction cost, while Martin and Skouras apply a fifty basis point transaction cost per one way, and a ten basis point transaction cost per one way, respectively.

Lee et al. find that day trading all nine exchange rates produces positive mean profits, but only one exchange rate, from Taiwan, yielded statistically significant positive profits after transaction costs were applied. Martin discovered that day trading produced positive mean returns for ten out of the twelve currencies considered. Martin also found that his day trading strategy did not produce significantly superior risk adjusted returns than a buy and hold strategy, that in terms of risk, both day trading and buy and hold offer similar results. Skouras compares several moving averages with different percentage bands, utilizing the optimal in sample moving average and percentage band combination. Skouras discovers that after transaction costs are considered, his optimized day trading strategy of the DJIA stock index beats a buy and hold

strategy on average of six basis points year, which is a statistically insignificant level of outperformance, probably produced by chance. Olson discovered that excess returns produced from a moving average based day trading strategy, compared to a buy and hold strategy, have declined over time. During the 1980's, Olson found that excess returns, after transaction costs, average approximately three percent for all eighteen currency exchange rates considered, while in the 1990's, the excess returns decrease to an average of about zero percent for all eighteen currency exchange rates. Olson's discovery in his research is fleshed out in detail by author Andrew Lo (2004), father of the theory known as The Adaptive Market Hypothesis. Lo's theory states that certain technical signals are more successful in specific time periods than in others because market efficiency is dynamic not static, market efficiency changes because of changing market structure and the variable influence that central governments/banks extol on the markets at any given time.

Day & Wang (2002), Kwon & Kish (2002), Neely (2002), Saacke (2002), Fang & Xu (2003), and Sapp (2004) day trade: the DJIA, the NYSE value-weighted index, four foreign currency exchange rates, the U.S. dollar/German mark currency exchange rate, the Dow Jones Utilities, Industrial, and Transportation Averages, and the German mark and Japanese yen currency futures respectively. All authors test variations of the simple moving average trading strategy. Kwon and Kish create a moving average indicator for volume and combine it with the moving average indicator for price, Fang and Xu do the same, but also add a time series model. Day and Wang consider a five basis point one-way transaction cost, Saacke considers a five basis point round trip transaction cost, while Kwon and Kish and Neely do not adjust for transaction costs. Fang and Xu consider a round trip transaction cost of one hundred one basis points, and Sapp considers a one-way transaction cost of fifty basis points. All authors compare their day

trading results against a buy and hold strategy, except Sapp, who compares his trading results against the Sharpe ratio of the S&P 500.

Day and Wang's results also add credence to Andrew Lo's Adaptive Market Hypothesis, in two sub periods in the authors' research, they find opposing results. From 1962-86, Day and Wang are able to capture statistically significant returns in excess of a buy and hold strategy; even after transaction costs are considered. From 1987-96, however, the results are uninspiring, excess returns turn out to be statistically insignificantly different than zero, after transaction costs are considered. Kwon and Kish discover that combined moving averages of both price and volume captured positive statistically significant excess returns, although the authors do not consider transaction costs. Neely found that a simple moving average rule captured statistically significant returns in excess of a zero mean profit benchmark, although no transaction costs are applied in his work. Neely noticed that the coincidence of central bank intervention in the currency market precedes the periods in which he captures his highest day trading profits. Saacke tested all possible simple moving averages from two days to five hundred days of historical data, concluding that simple moving averages that utilize more than one hundred seventy days of historical price data capture statistically significant returns in excess of a buy and hold strategy, after transaction costs are considered. Saacke is amongst the first researchers to utilize a bootstrap simulation method, concluding that long term moving averages generated abnormal profit, which neither a bootstrap simulation nor a random walk model could account for. Saacke concluded that higher profits do in fact coincide with time periods immediately before central bank intervention. Fang and Xu's results indicate that a time series model is best suited for bearish markets, while technical analysis performs best in a bull market. The researchers also conclude that by combining a time series model to a simple moving average,

higher and more consistent returns can be realized, after adjusting for transaction costs. Sapp discovers that before 1995, simple moving averages, after adjusting for transaction costs, captured statistically significant returns in excess of the market. After 1995, Sapp discovers that simple moving average rules, after adjusting for transaction costs, capture statistically insignificant returns in excess of the market. Sapp concludes that the coincidence between central bank intervention and statistically significant excess returns cannot be rejected as merely coincidental.

The notion of utilizing genetic programming algorithms as a means of capturing persistent economic profits by trading the financial markets produced a series of academic research papers focused on the, at the time, novel idea. Neely, Weller, & Dittmar (1997), Allen & Karjalainen (1999), Fyfe, Marney, & Tarbert (1999), Neely & Weller (1999), Wang (2000), Neely & Weller (2001), Korczak & Roger (2002), Ready (2002), Neely (2003), Neely & Weller (2003), and Roberts (2003) day trade: six exchange rate futures contracts, the S&P 500 index, various U.K. stocks, four exchange rate futures contracts, S&P 500 futures contracts, four exchange rate futures contracts, the CAC40 Index of the Paris Stock Exchange, the DJIA, the S&P 500, four exchange rate futures contracts, and corn, soybean, and wheat futures contracts, respectively. All authors day trade their respective securities in order to analyze the profitability of various genetic programming algorithms as day trading tools in the financial markets. All authors consider the effects of transaction costs: ten basis points per round trip, twenty-five basis points per one way trip, one hundred basis points per one way trip, ten basis points per round trip, a flat two hundred seventy-five dollars per one way trip, ten basis points per round trip, twenty-five basis points per one way trip, thirteen basis points per one way trip, twenty-five basis points per one way trip, three basis points per one way trip, and a flat twenty-five dollars per round trip,

respectively. All authors compare their day trading results against a buy and hold strategy, all with the exception of Roberts who compares his day trading strategy to a zero mean profit benchmark.

Neely, Weller, & Dittmar (1997) discover that the optimized trading rules that the genetic programming algorithm developed in sample capture statistically significant returns out of sample, after transaction costs are considered, for all one hundred trading rules that the genetic programming algorithm developed. Neither a random walk model, nor the bearing of the fair compensation of day trading risks could explain the mean excess return across all optimized trading rules. Allen & Karjalainen (1999) discover that the trading rules developed by their genetic programming algorithms produce a negative mean excess return for six out of the ten sub periods, after transaction costs considered. The authors conclude that trading rules developed by genetic programming algorithms cannot consistently beat the buy and hold strategy. Fyfe, Marney, & Tarbert (1999) discover that the fittest of all trading rules developed by their genetic programming algorithms captured statistically significant returns in excess of a buy and hold strategy, after adjusting for transaction costs. When the same trading rule was tested via a bootstrap simulation, the test indicated that the returns are indeed statistically significant.

Neely & Weller (1999) discover that the one hundred optimized trading rules produced from the authors' genetic programming algorithms capture positive mean returns, after adjusting for the effect of commissions, however, no trading rule generated excess returns that were statistically significant. Wang (2000) discovered that the optimized trading rules produced from his genetic programming algorithms outperformed the buy and hold strategy 47.5% of the time, after adjusting for transaction costs. Wang concluded that because of the inconsistency of his results, that the trading rules developed by his genetic programming algorithm(s) are not

statistically significant, nor do these trading rules hold anticipatory market powers. Neely & Weller (2001) developed optimized trading rules utilizing a genetic programming algorithm to take advantage from Federal Reserve forex intervention. Interestingly the results are mixed. Prior to 1993, the authors note that statistically significant returns in excess of a buy and hold strategy, after transaction costs considered, were attainable by utilizing any of the optimized trading rules developed by the authors' genetic programming algorithms. After 1993, however, the authors note that no optimized trading rule is able to capture statistically significant excess returns.

Korczak & Roger (2002) discover that for nine out of ten sub periods, the optimized trading rules produced from the authors' genetic programming algorithms beat a buy and hold strategy, after transaction costs are considered. The authors do not mention any test for statistical significance, merely stating that their results are stable over time. Ready (2002) discovered that every single trading rule his genetic programming algorithm produced outperformed a buy and hold strategy as well as multiple simple moving average rules, after transaction costs considered. Neely (2003) discovered that the optimized trading rules developed by his genetic programming algorithm only outperformed a buy and hold strategy, after transaction costs considered, during the in sample period, and by about five percent. Out of sample, the optimized trading rules underperformed a buy and hold strategy. Also, Neely analyzed his day trading results in terms of risk-return efficiency against a buy and hold strategy, concluding that a buy and hold strategy produces more risk efficient returns over the long run. Neely & Weller (2003) discover that the optimized trading rules produced from a genetic programming algorithm, when transaction costs are considered, the day trading strategy more or less breaks even with a buy and hold strategy. Roberts (2003) discovered that the best of ten optimized trading rules developed by his genetic programming algorithm produce statistically significant results for wheat futures contracts out of

sample, after transaction costs are considered, but not for corn, nor soybean contracts. Roberts concludes that because statistical significance is only present for one out of three contracts considered, that there is no strong evidence for the predictive power of trading rules developed by genetic programming algorithms.

Academic researchers, for the first time, begin to utilize Halbert White's Reality Check Test to determine whether excess returns are statistically significant, since the results of Lukac & Brorsen (1990) imply that technical trading rules generate returns that are abnormal, being leptokurtotic with positive skew, which makes z tests useless as a means of testing statistical significance. Sullivan, Timmermann, & White (1999), Qi & Wu (2002), and Sullivan, Timmermann, & White (2003) day trade: DJIA & S&P 500 futures contracts and seven currency exchange rate futures contracts respectively. The authors test: filter rules, simple moving price and volume averages, support and resistance levels, price channels, trading range break out rules, and calendar based trading rules. Only Qi & Wu adjust for the cost of commissions, applying a four basis point transaction cost per one-way trip. All authors compare their day trading results against a buy and hold strategy; and all authors apply a Bootstrap Reality Check Test in order to test the statistical significance of their excess return distribution(s).

Sullivan, Timmermann, & White (1999) discover that the best trading rule, a five day simple moving average, captured an average annualized excess rate of return of ten percent, averaged across both DJIA and S&P 500 futures, without adjusting for transaction costs. After applying the Reality Check Test, the authors deduce that their excess returns are not derived from data snooping, and are in fact statistically significant. However, the authors also find that during the most recent sub period, the best trading rule captured an average annualized excess rate of return of negative five percent, also the mean excess rate of return during the most recent

sub period was found to be statistically insignificant via the Reality Check Test, implying that the best trading rule's statistical significance across all time intervals must be derived from time intervals prior to the most recent interval. The authors conclude that the best technical signal's predictive power has therefore decayed over time. Qi & Wu (2002) discover that the best trading rule, a simple moving average, captured statistically significant and positive mean excess returns, after adjusting for transaction costs, against a buy and hold strategy via White's Reality Check Test. The authors conclude that the best trading rule's predictive power appears robust across different currencies and different Bootstrapping significance levels. Sullivan, Timmermann, & White (2003) discover that the best trading rule, a calendar based trading rule, produces positive mean excess returns against a buy and hold strategy, for both DJIA and S&P 500 futures contracts, although no transaction costs are accounted for. The authors conclude that because both mean excess rates of return, four and two percent respectively, were found to be statistically insignificant via the Reality Check Test, that none of the technical signals considered hold consistent forecasting abilities. Although the results of Sullivan et al. ('99 & '03) and Qi & Wu (2002) are mixed, their research techniques have helped to create a framework for future researchers to continue testing various technical trading strategies.

Day trading with the assistance of price chart patterns, the oldest form of technical analysis, was once deemed too subjective to be objectively tested, but nearing the close of the twentieth century, academia has discovered a way to finally test price chart patterns both scientifically and conclusively. Curcio, Goodhart, Guillaume, & Payne (1997), Caginalp & Laurent (1998), Chang & Olser (1999), Guillaume (2000), Lo, Mamaysky, & Wang (2000), Osler (2000), Leigh, Paz, & Purvis (2002), Leigh, Modani, Purvis, & Roberts (2002), Dawson & Steeley (2003), Lucke (2003), and Zhou & Dong (2004) day trade: three currency futures

contracts, all world equity closed end funds and all S&P 500 stocks, six currency futures contracts, three currency exchange rate futures contracts, all NYSE, AMEX, and NASDAQ stocks, three currency futures contracts, the NYSE composite index, the NYSE composite index, the FTSE 100 and FTSE 250, five currency futures contracts, and all stocks listed on the NYSE, AMEX, and NASDAQ indices, respectively. The authors test: support and resistance levels, candlestick patterns, head and shoulders, simple moving averages, momentum oscillators, price triangles, rectangles, trading range break out rules, several tops and bottoms, and various flag price chart patterns, in order to determine if price chart patterns capture persistent excess returns. Only Curcio, Goodhart, Guillaume, & Payne (1997), Caginalp & Laurent (1998), Chang & Olser (1999), and Guillaume (2000) adjust for transaction costs: utilizing twenty basis points per round trip, thirty basis points per round trip, five basis points per round trip, and fifteen basis points per round trip, respectively. All authors compare their day trading strategies to a buy and hold strategy consisting of the relevant securities.

Curcio, Goodhart, Guillaume, & Payne (1997) discover that only nine percent, four out of thirty-six, of all the support and resistance levels tested generated positive statistically significant mean excess returns, after transaction costs considered. The authors conclude that because most of the support and resistance levels tested either captured statistically insignificant mean excess returns, or negative statistically significant mean excess returns, that support and resistance levels do not have persistent forecasting abilities in the forex markets. Caginalp & Laurent (1998) find that candlestick reversal indicators hold statistically significant anticipatory market power across all stocks considered, after adjusting for transaction costs. The authors are able to capture an average annualized mean excess rate of return of over three hundred percent across all S&P 500 stocks. The immense success of Caginalp & Laurent (1998) illustrates that

short-term price changes are in fact predictable, if one utilizes the right signal, with the right parameters, combined with the right strategy.

Chang & Olser (1999) discover that head and shoulders trading rules do not produce significant excess returns across all six-currency futures. Both the three momentum oscillator rules and five simple moving average rules generated positive statistically significant mean excess returns across all six currency futures, after adjusting for transaction costs. Thus, the authors conclude that the best performing technical signals are able to predict short-term changes across various forex markets. Guillaume (2000) tests his strategy by utilizing two sample periods. Interestingly, the first sample period saw all trading range break out rules considered produce positive statistically significant mean excess returns, after adjusting for transaction costs. The second sample period produced opposite results, none of the trading rules considered generated statistically significant excess returns. Guillaume concluded that the predictive power of the best performing technical signals is unstable, decaying over time, usurped perhaps by other yet unknown technical signals. Lo, Mamaysky, & Wang (2000) discover that no statistically significant excess returns can be captured by any trading rule they consider. Osler (2000) discovers that the best support and resistance levels generated statistically significant excess returns across all three currency futures contracts considered, although no adjustments for transaction costs are considered. Therefore, because no transaction costs are considered, it is conceivable that Osler's significant results are spurious. Leigh, Paz, & Purvis (2002) discover that all flag charting patterns considered captured positive statistically significant mean excess returns, though no transaction costs are accounted for. Thus, the claim that flag charting patterns can predict price paths is illegitimate without the real world consideration of transaction costs. Leigh, Modani, Purvis, & Roberts (2002) discover that when the NYSE Composite's price

exhibits a bull flag chart pattern, purchasing the index for at least one hundred days, after transaction costs, generates a positive statistically significant annualized mean excess rate of return of 5.8%. Dawson & Steeley (2003) discover that the same price chart patterns: head and shoulders, tops and bottoms, triangles, and rectangles, employed by Lo et al. (2000), on average, capture negative statistically insignificant mean excess returns, after transaction costs. Lucke (2003) discovers that the head and shoulders price chart pattern fails to capture statistically significant mean excess returns, after transaction costs considered. Zhou & Dong (2004) discover that the price chart patterns employed by Lo et al. (2000), when applied to stocks trading below an average price of two dollars a share, are able to capture statistically significant mean excess returns of three percent per annum, after transaction costs. The same technical signals do not capture statistically significant excess returns for stocks trading above an average price of two dollars a share. The authors conclude that for whatever reason, penny stock prices seem to move about more predictably than their more expensive counterparts.

Neural networks, machine learning, artificial intelligence, and random forests, are all the cutting edge of computer problem solving software, it is therefore no surprise that researchers interested in technical analysis and skilled at developing artificial intelligence models have taken the latest and greatest in computational analysis and applied it to trading the financial markets. Technical analysis research in this field tends to prioritize the model's sign prediction ability. Researchers who utilize an artificial neural network model have been quite successful at predicting daily market directional changes. Academic papers such as: Gencay (1998), Gencay & Stengos (1998), Gencay (1999), Fernandez, Rodriguez, Gonzalez, Martel, Sosvilla-Rivero (2000), Sosvilla-Rivero, Andrada-Felix, & Fernandez, Rodriguez (2002), and Fernandez, Rodriguez, Sosvilla-Rivero, & Andrada-Felix (2003), illustrate that artificial neural network

models tend to beat a buy and hold strategy. The neural network models developed by the aforementioned researchers, on average, are able to predict daily market trends correctly 57% of the time. The results of neural network based technical analysis add credence to the argument, which postulates that security prices move about predictably.

Today, technical analysis research that does not focus on the subject of artificial neural network modeling seeks instead to further improve the alpha generating ability of: filter rules, moving averages, relative strength indicators, combined signal models, CRISMA models, and Markov Chain models. Most often times, the most successful technical signal tends to be the simple moving average rule, in fact most Markov Chain models, combined signal models, and in fact all CRISMA models, incorporate simple moving average rules, to a varying degree. Throughout history, the ability for a technical signal(s) to capture consistent, statistically significant returns appears to be a dynamic struggle; positive excess returns persist for a while and then disappear. The random walk hypothesis implies that technical signals are expected to occasionally outperform a given benchmark some of the time, though not consistently. Some technical signals have been found to capture statistically significant returns in excess of a given benchmark over a robust sample period, and across multiple securities/markets, something that the random walk hypothesis cannot explain. However, since most technical signals' relative outperformance persists for only a short time, and only for specific securities, many adherents of the random walk hypothesis argue that if a technical signal does not capture excess returns consistently across several markets and over a long enough sample period, then that signal does not truly have forecasting skills. For most, the results are inconclusive, the random walk hypothesis is perhaps the most elegant model, but there is evidence that financial markets, at least some of the time, exhibit predictability that can be exploited by specific technical signals.

Historically, the best performing technical signals across the academic literature are: simple moving averages, filter rules, and trading range break out rules. These signals have historically offered the highest and most consistent profits across multiple securities, markets, and sample periods, supporting the argument that the financial markets may be somewhat predictable, even if the predictability arguably decays over time. In the first decade of the twenty-first century, Camillo Lento wrote numerous papers detailing the success of his infamous Combined Technical Signal Approach and its ability to earn consistent economic profit on equity indices from equity markets around the world: USA, Canada, 8 Asian-Pacific Markets, and Greece. However other authors find that consistent economic profit cannot be generated over the long run on any equity indices, perhaps because few authors combine their signals, which may amplify their signals' predictive accuracy.

Authors Cheol-Ho and Scott Irwin in their 2004 and 2007 papers, and Irwin, Lukac, and Brorsen, (1988), propose that the only justification for any short term economic profit generated from technical analysis must be that the markets are in temporary states of short term disequilibrium where information shocks are not instantaneous, but rather prices exhibit stickiness. The authors compared individual technical signals rather than utilizing a combined technical signal approach. Ho and Irwin state that consistent short run profit cannot be generated on US stock market indices from 1974-2003 by using any individual technical signals that the authors consider, however, consistent profit can be generated on commodity futures from 1974-1984, but not from 1985-2003 by using the same individual technical signal methodology. However, Lento states that from 1950-2008, his combined technical signal approach consistently generates short run economic profit on the S&P 500 index. Therefore, the ability to capture consistent economic profit must depend on the usefulness of the applied signal(s)/strategy.

Since volatility is the quantification of an asset's risk, it is only reasonable to assume that researchers would one-day test volatility for its forecasting abilities. Academic researchers have only recently documented the utility of an asset's volatility as a technical signal; Giot (2006) concludes that there exists a positive relationship between an asset's implied volatility and forward-looking returns. Giot tested extreme VIX levels and S&P 500 forward returns, discovering that whenever implied volatility reaches a level that is significantly higher than its historical average, one can expect the underlying asset's future returns to also be higher than its historical average. Therefore, mining technical signals from a security's implied volatility index and combining the signals together, since the debut of the VIX and its sister indices, is the logical progression for testing the combined technical signal approach on the equity markets.

Kozyra and Lento (2011) argue that perhaps the forecasting accuracy of the Combined Signal Approach can be amplified by utilizing VIX data to increase profitability. The authors day trade: the S&P 500 index, the NASDAQ composite, and the DJIA over a ten year period, from January 1, 1999 to January 1, 2009, using technical signals derived from the VIX. The authors compare their day trading strategy to a buy and hold strategy for each equity index. Excess returns are computed with transaction costs of four basis points per round trip considered. Interestingly, the authors do not utilize the combined signal approach as a single indicator. Instead, Kozyra and Lento utilize the three variations of the three technical signals, which compose the combined signal approach, independently. The authors discover that six out of the nine trading rules considered beat a buy and hold strategy, after transaction costs considered, throughout the whole ten-year sample period. The authors utilize a bootstrap simulation in order to test the statistical significance of their excess returns, realizing that only the one and two percent filter rules offer statistically significant mean excess returns, and only for the S&P 500

index and the DJIA. Kozyra and Lento conclude that market volatility can be utilized to improve the profitability of technical analysis.

The technical analysis literature that focuses on volatility is relatively young, but booming, with over two hundred thousand research papers written on the subject since the early 1990's. In essence, the research focuses on testing volatility for its predictive utility through a barrage of statistical tests. Kozyra and Lento, much like most of the technical analyst authors focused on the subject of volatility, neglect to consider the effect of dividends when comparing their specific day trading strategy to a buy and hold strategy. This thesis takes into account the effect of dividends when comparing each strategy's annualized returns, considering the effect crucial to understanding whether a specific day trading strategy is truly more profitable/risk-efficient than a buy and hold strategy. Most authors, along with Kozyra and Lento, also neglect to perform a statistical test to determine whether their excess returns conform to a normal distribution. This thesis utilizes a Jarque-Bera significance test to uncover whether excess returns derived from a specific day trading strategy conform to a normal distribution, as assumed by Jensen (1968). Most authors, including Kozyra and Lento, never consider whether their strategy is persistently more risk efficient than a buy and hold strategy. This thesis ascertains the statistical significance of a specific day trading strategy's excess Sharpe Ratio against a buy and hold strategy's Sharpe Ratio via a bootstrap simulation. Kozyra and Lento neglect to consider the Combined Signal Approach as a single indicator, instead the authors focus on comparing the individual signals, which make up the Combined Signal Approach. This thesis utilizes the nine technical signals within the Combined Signal Approach as single votes within a simple majority decision-making mechanism. Fundamentally, Kozyra and Lento evaluate whether a specific stock market's implied volatility index can be utilized to day trade multiple equity indices within

said specific stock market. This thesis examines whether the implied volatility of an underlying asset is useful for day trading the underlying asset. The difference, this thesis tests the forecasting power of multiple implied volatility indices to day trade their respective underlying equity index, instead of testing the forecasting power of just one implied volatility index, the VIX, to day trade multiple equity indices. Ultimately, this thesis contributes to the field of technical analysis by ascertaining, with statistical support, whether mining historically successful technical signals from implied volatility indices has any practical applications for day trading equity indices.

CHAPTER 4

METHODOLOGY

The Combined Technical Signal Approach employed in this thesis is the same approach applied by Lento (2008). Where three different moving averages, three different filter rules, and three different trading range break out rules are combined into a single signal. The combined signal initiates a buy or sell response only when the majority of individual signals agree on either buying or selling the underlying asset on a given day. Buy/sell decisions regarding each underlying equity index are made at the open of every trading day. Every trading day, for the day trading strategy, the purchase/short-sale of every stock index is filled at the open price plus/minus the bid-ask spread, and the position is liquidated at the closing price plus/minus the bid-ask spread. Historical bid-ask spreads are determined by extrapolating current bid-ask spreads on the exchange traded funds of the underlying stock indices, with each bid-ask spread averaging around one penny per transaction, *Why SPY: Size, Liquidity, and Low Cost of Ownership* (2014).

Transaction costs are fixed at ten dollars per transaction. Thus on a daily basis, the average day trader with just over one hundred thousand dollars to trade, spends about twenty dollars per day, or about five percent per annum on transaction costs alone, *Reviewing the Biggest Online Brokers* (2013). While the average retail, buy and hold investor, buys once and sells only once, therefore transaction costs are neglected from the calculations of returns for the buy and hold investor. For the average day trader, transaction costs at the end of the year total approximately five thousand dollars, or about five percent. Therefore, excess returns, when calculated to consider transaction costs, assume that an extra five percent is deducted annually from the excess returns of a day trader's strategy against the buy and hold strategy. Day trading

each stock index begins two hundred-one days after each implied volatility index's first trading day, in order to allow for a two hundred day simple moving average and two hundred day trading range break out rule to be calculated and utilized by the Combined Signal Approach.

In general, buy and sell signals are constructed based on either a momentum or mean reversion strategy. Technical analysis is divided between two approaches: a momentum based trading and mean reversion based trading. Each signal in the CSA can be modified to fit either trading strategy. For example, if the opening price of a volatility index is greater than an x day moving average, according to momentum theory, volatility is expected to rise. According to mean reversion theory, volatility would be expected to fall in the given scenario. In pretesting we identified that the volatility based CSA with a momentum strategy outperformed the volatility based CSA with a mean reverting strategy and the equity based CSA with a mean reverting strategy outperformed the equity based CSA with a momentum strategy. Therefore, in this research we employ a momentum strategy for the volatility based CSA and a mean reverting strategy for the equity based CSA.

One third of the combined signal approach utilizes simple moving averages in order to compute buy/sell orders. The three simple moving averages employed in this thesis: 50, 150, and 200 days, are constructed using past closing prices. A simple moving average is computed by adding the closing price of a security over a number of days, 50, 150, and 200 days are utilized in this thesis, and dividing the total sum by the number of days. For the volatility based CSA, which utilizes momentum theory, a buy signal is initiated when the open price of the implied volatility index is below the simple moving average while a sell signal is initiated when the open price of the implied volatility index is above the simple moving average. Normally, a buy signal is initiated when the open price is above the simple moving average, however a volatility index

moves inversely to its corresponding equity index, therefore buy signals are initiated when volatility opens below its historical average, simply put, buy the stock market when volatility is historically low, and sell the stock market when volatility is historically high. According to momentum strategy, when volatility is low, the underlying equity index should rise, as long as volatility continues to stay low, conversely, momentum strategy indicates that when volatility is high, the underlying equity index should fall, as long as volatility continues to stay high.

The three Filter Rules applied by the Combined Signal Approach utilize the prior day's high and low prices in comparison to the current day's opening price, to determine a buy/sell signal. The filter rule follows if statement logic. According to momentum theory, buy if the opening price is strictly greater than x percent above the previous day's low sell otherwise. 1%, 2%, and 5%, are the filters used in this thesis, as these filter rules are the rules that Camillo Lento utilized when he first tested the Combined Signal Approach. However, because the technical signals are applied to implied volatility indices in this thesis, which move contrarian to their respective equity indexes, the reverse logic is applied. Buy signals are initiated from the filter rule when the opening price of the implied volatility index is lower than x percent below the previous day's high and sell signals are initiated otherwise. The only difference between each filter rule is the different percentages each one utilizes to determine buy/sell signals, based off the previous day's extreme price levels. The final signal employed in the combined signal approach only initiates buy/sell signals when a long-term support/resistance level has been broken.

Similar to the filter rule, the trading range break out strategy seeks to identify support and resistance levels. The main difference between the two strategies is that the latter never trades while the price is between the identified support/resistance levels. Only when the price is below

its 50, 150, or 200-day low does the trading range break out strategy initiate a sell signal, and only when the price is above its 50, 150, or 200-day high does the trading range break out strategy initiate a buy signal. The logic of the trading range break out rule is that if the price falls/rises below/above a support/resistance level, that momentum will drive the price away from the range, changing previous support levels into resistance levels and vice versa. Again, because implied volatility indices are utilized in this thesis, the logic is reversed. Buy signals are initiated from the trading range break out rule when implied volatility falls below a 50, 150, or 200 day low, and sell signals are initiated from the trading range break out rule when implied volatility rises above a 50, 150, or 200 day high.

The following equations are for the three technical signals, which are employed by the Combined Signal Approach. The equations are similar to the ones utilized by Lento (2008), however, they have been modified in order to be applicable to implied volatility. Equation (1) demonstrates the simple moving average signal equations.

$$a_n = \begin{cases} 1 & P_t \leq (P_{t-1} + P_{t-2} + P_{t-3} + \dots + P_{t-n})/n \\ 0 & P_t > (P_{t-1} + P_{t-2} + P_{t-3} + \dots + P_{t-n})/n \end{cases} \quad (1)$$

where P_t is the opening price of the implied volatility index, 1 indicates a buy signal and 0 indicates a sell signal. I will implement 50, 150, and 200 day moving average signal equations.

P_t is the opening price of the implied volatility index. Thus it reads, if the n –moving average sequence of closing prices is less than the opening price, then sell the equity index, because implied volatility is relatively high. And vice versa, if the n –moving average sequence of closing prices is greater than the opening price, then buy the equity index, because implied

volatility is relatively low. Since implied volatility is a contrarian indicator, low volatility means the underlying asset's price is expected to increase, while high volatility means the underlying asset's price is expected to decrease.

Equation (2) demonstrates the filter rule equation.

$$b_p = \begin{cases} 1 & P_t \leq (1 + p/100)P_{t-1}^L \\ 0 & P_t > (1 + p/100)P_{t-1}^L \end{cases} \quad (2)$$

If the opening price of the volatility index is p percent greater than the previous day's low, P_{t-1}^L , then sell the equity index ($b_p = 0$). Otherwise, buy ($b_p = 1$). I implement a 1, 2, and 5 percent filter rule in this analysis.

Equation (3) demonstrates the trading range breakout signal equations.

$$c_b = \begin{cases} 1 & P_t \leq \max(P_{t-1} + P_{t-2} + P_{t-3} + \dots + P_{t-b}) \\ 0 & P_t > \max(P_{t-1} + P_{t-2} + P_{t-3} + \dots + P_{t-b}) \end{cases} \quad (3)$$

If the opening price of the volatility index is greater than the maximum of the previous b days, then sell ($c_b = 0$), otherwise buy the equity index. I implement a 50, 150, and 200 day trading range breakout signal in this analysis.

Now that the signals are defined that make of the components of the combined signal, I define the Master Equation, ME , that determines whether the combined signal produces a buy signal or a sell signal.

$$ME = \begin{cases} 1 & a_{50} + a_{150} + a_{200} + b_1 + b_2 + b_5 + c_{50} + c_{150} + c_{200} > 4 \\ 0 & a_{50} + a_{150} + a_{200} + b_1 + b_2 + b_5 + c_{50} + c_{150} + c_{200} \leq 4 \end{cases} \quad (4)$$

So that ME produces a buy signal if at least 4 of the 9 component signals produce a buy signal.

At the opening of every trading day, the implied volatility indices are analyzed by the Combined Signal Approach in order to produce buy/sell signals, with which long/short positions are initiated on the underlying equity index. The daily excess return, alpha, between the day trading strategy and the buy and hold strategy, per each stock index, is measured as the daily net rate of return of the day trading strategy minus the daily net rate of return of the buy and hold

strategy. Transaction costs and bid-ask spreads are subtracted from the daily returns of each strategy as transactions occur. Dividends are derived from the historical average dividend yield that the specific equity index generates over the sample period. Dividends are added only to the annualized returns of each equity index for the buy and hold strategy, in order to calculate excess returns with dividends considered, after transaction costs are factored for. Each sample distribution of excess returns is scrutinized via the Jarque-Bera goodness of fit to normality test with a 95% confidence interval to determine if the strategy's alpha conforms to a normal distribution, with/without considering for transaction costs/dividends. The Jarque-Bera test utilizes each excess return series' mean, median, skewness, and kurtosis, in order to test for the likelihood that the return series conforms to a normal distribution. After which White's Reality Check Test is utilized to test for the statistical significance of excess returns, both with and without dividends/transaction costs considered.

Excel is the software package utilized in this research in order to derive the daily rates of return per strategy from daily price data that was exported from Google Finance into Excel. Buy and hold daily rates of return are calculated simply from equity index price data. Excel based if statements were utilized in order to create buy and sell signals from daily price data, from which the day trading strategy's returns were calculated, based on the technical signals' discretion. Lastly, summary statistics of each strategy's data series was compiled, all done on Excel, in order to perform statistical significance tests. In order to conduct a moving block method of bootstrapping in conjunction with Halbert White's Reality Check Test, I utilized MatLab, specifically I modified code written by and made public by Kevin Sheppard, entitled *Technical Trading: Fool's Gold? Forecast Evaluation with Many Forecasts* (2014).

Moving Block Bootstrapping Method & Halbert White's Reality Check Test Equation(s)

Let $X_0 = \{x_{0,t}, x_{0,t+1}, \dots, x_{0,t+n}\}$ be a weakly dependent time series in which each observation is auto-correlated to the previous observation in the time series. The auto-correlated pairs of observations are utilized as building blocks for replicating the original time series.

Suppose there is a table of randomly generated numbers. Each column in the random number table has the same number of random numbers as the original data sample, X_0 , has auto-correlated data pairs. A random number from the table indicates which numerically designated data pair is next in creating a random re-sampling of the original time series. Going from one random number to the next in the table is equivalent to drawing the auto-correlated data pairs randomly with replacement from the original time series. The auto-correlated data pairs form replications of the original data sample; each replicated time series preserves the inherent dependence of the original time series. Repeating the process creates random re-samples of the original data sample.

As long as the simulations are composed of weakly dependent and randomly generated observations, the higher the number of simulations, X_i , the closer the mean of all the re-samples' means and the mean of all the re-samples' standard deviations conform to the first two moments of a normal distribution,

$$\text{As } X_i \rightarrow \infty, \text{ the } \mu(\mu\{X_i\}) \text{ and the } \mu(\sigma\{X_i\}) \rightarrow N(\mu, \sigma).$$

The average of the averages and the average of the standard deviations of the excess return series simulations are scrutinized by a two-tailed z test with a 95% confidence interval in order to determine whether excess returns are statistically significant, before and after dividends/transaction costs are considered. A random variable is defined by its mean and standard deviation, as well as the distribution from which it was drawn, the two-tailed z statistics

test is only applicable to normally distributed random variables, what the moving block bootstrapping method does is it transforms our abnormally distributed random variable, alpha, the excess return of the day trading strategy over the buy and hold strategy, and normalizes it so that White's Reality Check Test, a two-tailed z test, may determine statistical significance.

The Reality Check Test is also applied to determine whether the CSA generates consistently greater Sharpe Ratio(s) than a buy and hold strategy's Sharpe Ratio(s). The Sharpe Ratio compares the ratio of an investment's mean rate of return to the standard deviation of the rate of return, in order to quantify a particular strategy's risk/reward efficiency. The Sharpe Ratio is a method of quantifying how risk/reward efficient a trading strategy is. Excess Sharpe Ratio is merely defined as the trading strategy's Sharpe Ratio minus the Buy & Hold Sharpe Ratio. In order to test for the statistical significance of excess Sharpe Ratios, ten thousand bootstrap simulated weakly dependent and randomly generated with replacement excess return series are produced for every equity index and for both trading strategies. Each simulation of the original time series produces one Sharpe Ratio. As the number of Sharpe Ratios produced increases, the average and standard deviation of the simulation based Sharpe Ratios tend towards normality. Normally distributed parameters can be utilized in a two-tailed z statistics test, which ultimately reveals whether Sharpe Ratios generated from a trading strategy are statistically significantly different than Sharpe Ratios produced from buying and holding an equity index. Sharpe Ratios are calculated before and after considering transaction costs, but are also calculated with/without considering dividends. A two-tailed z test with a 95% confidence interval is applied to the normalized parameters derived from the excess Sharpe Ratio simulated sample distributions, with/without transaction costs, and with/without dividends, in order to test whether the excess

Sharpe Ratio in all simulations is consistently greater than zero, which signifies persistent outperformance of the market.

Sharpe Ratio & Excess Sharpe Ratio Equations

$$\text{Sharpe Ratio} = R_p / \sigma_p$$

Where R_p is the annualized average net rate of return of the trading strategy, and σ_p is the annualized standard deviation of the trading strategy.

$$\text{Excess Sharpe Ratio} = \text{Day Trading Strategy's } (R_p / \sigma_p) - \text{Buy \& Hold Strategy's } (R_p / \sigma_p)$$

CHAPTER 5

DATA

The daily tracking of implied volatility indices began with the VXO in January 1986, the VIX began in January of 1990, the VXN in October 2000, and the VXD in October of 1997.

Therefore, in order to day trade each of the underlying stock indices using all of the technical signals implied by the corresponding implied volatility indices, trading must begin two hundred days after the first trading day on the volatility index. Daily rate of return data for both equity indices and implied volatility indices was pulled from the relevant price data via Google Finance.

Day Trading Strategy Daily Net Rate of Return

$$(\text{Equity Index's Closing Price} - \text{Equity Index's Opening Price}) / \text{Equity Index's Opening Price}$$

Buy & Hold Strategy Daily Net Rate of Return

$$(\text{Equity Index's Closing Price} - \text{Equity Index's Previous Closing Price}) / \text{Equity Index's Previous Closing Price}$$

Transaction costs, BAS, and dividends are factored into the rate of return results on an annual basis, and are thus not included in the above equation. The day trading strategy initiates positions at the open and liquidates them at the close. Thus, the daily net rate of return of the day trading strategy(s) is calculated as the current day's closing price minus the current day's opening price, all of that divided by the current day's opening price. For the buy and hold strategy, I compute the daily net rate of return as the difference between the current day's closing price and the previous day's closing price, all of that divided by the previous day's closing price,

since a buy and hold position holds overnight it must consider the previous day's closing price when computing the daily net rate of return. The main difference when computing the daily rate of return for a buy and hold strategy versus a day trading strategy, is that the prior strategy does not liquidate positions at the end of every trading day, the latter does. Therefore, transaction costs are neglected when determining the daily rate of return for the buy and hold strategy, but the calculation of the daily rate of return of the buy and hold strategy is taken in order to compare both strategies performances on a daily basis. The average dividend yields of every equity index across the total sample period are calculated and applied to the annualized mean rate of return of each buy and hold stock index. The reason dividends are factored into the returns for the buy and hold strategy and not the day trading strategy is because according to an article on the SEC's website entitled, *Ex-Dividend Dates: When Are You Entitled To Dividends* (2014), in order for an investor to be entitled to a dividend payment, said investor must at least own the stock at the time the markets close one business day before the ex-dividend date, up until the market opens on the ex-dividend date, said investor can sell his/her stock on the ex-dividend date and still be entitled to the dividend payment. However, the investor must hold the stock overnight, something that the day trading strategy does not do, therefore the day trading strategy is excluded from dividend payment eligibility.

CHAPTER 6

RESULTS

The Combined Technical Signal Approach, when utilized to mine daily directional indicators from several implied volatility indexes, captures positive mean excess returns against a Buy and Hold Strategy for all but one stock index, the Nasdaq Composite, after taking into account dividends and transaction costs. The strategy that yielded the highest average rate of return, after dividends and transaction costs considered, was the volatility based CSA trading strategy. Therefore, more focus is devoted to this strategy relative to the other two tested in this study.

Table 1 illustrates the relevant ticker symbols for each equity and volatility index from which relevant data is extracted. Table 2 compares the annualized daily net rate of return and annualized standard deviation for all three trading strategies and each of the four stock indexes, both before and after dividends and transaction costs. From Table 2 it is evident that the generally best performing trading strategy is the Volatility Based CSA strategy. For every equity index, besides the Nasdaq Composite, the Volatility Based CSA strategy consistently outperformed both the Buy and Hold Strategy and the Equity Based CSA trading strategy. Interestingly, the average return of the four equity indices generated by the Volatility Based CSA, even considering the poor performance of the strategy when day trading the Nasdaq, is greater, after transaction costs are factored in, than the average return of the four equity indices generated by the Buy and Hold strategy, even after dividends are added. What is perhaps the most noteworthy find is that the Volatility Based CSA trading strategy produces an average return,

that is more risk-efficient than the average return produced by the Buy and Hold strategy. Thus, it appears that utilizing buy/sell signals produced by an equity index's implied volatility index in order to day trade is generally a viable method to secure consistently greater and more risk-efficient returns than the buy and hold approach.

While the Volatility Based CSA illustrates the most impressive results across the entire sample period, it is imperative that the results of each strategy are further scrutinized via a Sub-Period Analysis. Table 3 illustrates a Sub Period Analysis for each trading strategy: Volatility CSA, Equity CSA, and Buy and Hold. The Sub Period Analysis indicates that during both Bull Markets, 2010-2015 and the most recent Bear Market 2008-2009, that the Volatility CSA, except for the NASDAQ Composite, produces consistently greater average returns than either the Buy and Hold Strategy or the Equity Based CSA strategy. Table 3 exhibits the Volatility Based CSA strategy's ability to consistently generate a positive average rate of return, when averaged across all four equity indices, before, during and after the Great Recession of 2008. The capability to reliably capture positive returns, regardless of the Market's Bull/Bear cycle is evidence of the power of the Volatility Based CSA as a day trading strategy, helping to add credence to technical analysis as a successful method to invest in the stock market.

Now we discover the results produced from each strategy. Table 4 illustrates each strategy's summary statistics, after factoring in both transaction costs and dividends. The results, the Volatility CSA for three out of four stock indices, all but the NASDAQ Composite, produced positive mean excess returns against the Buy and Hold strategy, after both dividends and transaction costs considered, though on average, the returns produced by the Volatility Based CSA are greater than both strategies. Also, on average the Volatility Based CSA strategy was also able to produce returns with greater risk efficiency than either the Buy and Hold Strategy or

the Equity Based CSA strategy. The Volatility CSA trading strategy correctly predicted the market's daily direction more accurately than the Buy and Hold Approach, by an average of about two percent.

Now we assess whether the excess returns discussed in Table 2 before are normally distributed so that we can assess the statistical significance of the excess return results. Table 5 exhibits the Jarque-Bera test statistic, at a 95% Confidence Interval, for both the Volatility Based and Equity Based CSA trading strategies. The results of Table 5 illustrate that none of the excess returns derived from day trading versus a buy and hold strategy belong to a normal distribution, both before and after considering dividends and transaction costs. The results of this test fall in line with the results of Lukac, Brorsen, and Irwin (1988), in that the excess returns generated by a day trading strategy exhibit positive skewness, except for the NASDAQ Composite, which exhibits negative skewness. Much like Lukac, Brorsen, and Irwin (1988), combined technical signals, which are based on implied volatility index indicators, do appear to exhibit definite leptokurtosis. Therefore, the apparent abnormality in the sample distributions of excess returns, evident from the Jarque-Bera test results in Table 5, appears to be due to both extreme skewness and extreme kurtosis. Due to the apparent abnormality in the original sample distributions, the statistical significance of the excess returns produced by the Volatility Based CSA against the Buy and Hold strategy cannot be determined by simply using a two-tailed z test. A two-tailed z test is only viable for normally distributed parameters, which are created only after generating simulated sample distributions, and applying the z test to the mean of the means and mean of the standard deviations of every simulated sample distribution, White's Reality Check Z-Test.

Now we determine whether our technical trading results are statistically significant, utilizing White's Reality Check Two-Tailed Z-Test. Table 6 displays the mean of means and

mean of standard deviations derived from the moving block method for bootstrapping simulated excess return sample distributions, Volatility CSA less Buy and Hold, which are utilized in order to determine whether the Volatility CSA can consistently generate excess returns which are statistically significantly different than zero for each equity index. The simulated excess returns differ in one interesting way from the original sample distribution. Generally, the simulated return distributions have lower average returns with a greater average standard deviation than the original sample distribution, implying that the volatility based CSA trading strategy may be less risk-efficient over a longer sample period than the initial sample period tested.

Now we assess, utilizing the normalized parameters from Table 6, whether or not the excess returns derived from the Volatility Based CSA trading strategy against the Buy and Hold strategy are statistically significant, using White's Reality Check Two-Tailed Z Test on the parameters generated from the simulated sample distributions. The significance results of White's Reality Check Two-Tailed Z Test in Table 7 indicate that the Combined Signal Approach is unable to generate statistically significant excess returns against a Buy and Hold strategy. The excess returns captured by the original Volatility Based CSA have lower p-values than the excess returns captured by the simulated Volatility Based CSA, meaning that the original results produced consistently better results than the simulation, albeit not consistent enough to be statistically significant. This implies that it is expected that if the Volatility Based CSA trading strategy was performed again, over a different sample distribution that the results would be worse than the original sample distribution indicates. In short the excess returns generated by the Combined Signal Approach are highly volatile, which prevents the excess returns from being consistent enough to pass a test for statistical significance. The Volatility

CSA is however able to produce statistically significantly greater Sharpe Ratios than the Buy and Hold strategy.

The excess Sharpe Ratio, presented in Table 8, calculated as the Sharpe Ratio of the Combined Signal Approach less the Sharpe Ratio of the Buy and Hold strategy, for every stock index besides the NASDAQ Composite, is positive, which indicates that utilizing a day trading technical strategy, versus a buy and hold strategy, on average, offers more risk efficient returns, even after considering for dividends and transaction costs. Table 8 also illustrates the simulated excess Sharpe Ratio, produced from the same bootstrapping simulation as the returns in Table 6. It is these simulated excess Sharpe Ratios that are utilized to produce the corresponding White's Reality Check Z Test Statistic in Table 7. Thus, while the CSA is unable to capture statistically significant excess returns, the strategy does provide a means to capturing statistically significant Sharpe Ratios in excess of the Buy and Hold strategy's Sharpe ratios. Strangely, Therefore, applying a day trading strategy that utilizes an equity index's implied volatility index to determine daily buy/sell signals is a feasible method to capturing returns with consistently greater risk-efficiency than a Buy and Hold strategy.

The same White's Reality Check Test is applied to the sub-period results from Table 4, in order to resolve whether the results from Table 4 have any statistical significance. Table 9 illustrates a simulation of the results from Table 4 by utilizing a moving block method for bootstrapping. Table 9 illustrates that the excess returns captured by the simulated Volatility Based CSA are lower than the original excess returns, while the excess returns captured by the simulated Equity Based CSA are greater than the original excess returns. This implies that one could expect lower average excess returns from the Volatility Based CSA if recreate the trading strategy over a different sample distribution. Also one would expect that attempting the Equity

Based CSA trading strategy over a different sample period would result in the Equity Based CSA capturing greater excess returns than the original sample distribution indicates. The simulated returns of the Sub Periods are then utilized to derive the statistical significance of the two CSA strategies against the Buy and Hold strategy, the results of which are located in Tables 10.

Table 10 illustrates White's Reality Check Z Test Statistics for the Volatility CSA and Equity CSA simulated Sub Period excess returns, respectively. The results indicate that although the Volatility CSA is usually able to generate greater returns against the Buy and Hold strategy, there is no Sub Period Analyzed where either day trading strategy produced statistically significant excess returns. Note, however, how the p-values from the Volatility Based CSA are consistently lower than the p-values of the Equity Based CSA, this indicates that the Volatility Based CSA is a better method than the Equity Based CSA in attempting to capture statistically significant returns. Regardless, the volatility-based day trading strategy, on average, both in reality and across several simulations, returns positive excess returns against the buy and hold approach, indicating that the technical analysis applied herein is a dependable technique for investing in equity markets.

Figure 1 illustrates the inverse correlation between all four equity indices and their corresponding volatility index. The strong inverse relationship between an equity index's performance and its implied volatility index's performance is crucial in understanding how technical signals derived from an implied volatility index are useful in predicting daily market directions. One major factor that is apparent in Figure 1 is the extreme inverse performance of every volatility index with its corresponding equity index. This visualization is helpful to understand why a momentum-based day trading strategy, as applied in the Volatility Based CSA, generally outperformed the other strategies.

The general outperformance of the Volatility Based CSA against the Buy and Hold approach is most evident in Figure 2. Figure 2 illustrates the annual rate of return of the volatility based CSA against the buy and hold strategy's annual rate of return. For every equity index traded, except the Nasdaq Composite, the Volatility Based CSA clearly surpasses the returns generated by the Buy and Hold strategy, even after factoring both dividends and transaction costs. While the Volatility Based CSA strategy clearly demonstrated superiority over the Buy and Hold approach, the same cannot be said for the Equity Based CSA, the results of which are displayed in Figure 3.

Figure 3 illustrates the annual rate of return of the Equity Based CSA versus the Buy and Hold strategy's annual rate of return. The Equity Based CSA, perhaps because it utilizing historical signals, unlike the forward-looking volatility based signals, fairs generally even with the Buy and Hold Strategy. Unlike the volatility based approach, the equity based strategy is unable to avoid the same negative effects of market crashes that plague the Buy and Hold approach, thus the Equity Based CSA strategy fails as a tool for technical analysis due to its lack of predictive ability.

Perhaps the best way to visualize the performance of the day trading strategies against the buy and hold approach is via equity curves. Figure 4 illustrates the equity curves of the equity based CSA verses the buy and hold strategy. Consider a day trading strategy with little in its ability to outperform a Buy and Hold approach, and then factor in the adverse effects of transaction costs, and the positive effect that dividends have on the Buy and Hold approach, and it is apparent that when considering between the two, a Buy and Hold approach clearly outperforms the Equity Based CSA. The equity curves indicate this truth in a most obvious way.

The opposite can be said for the equity curves of the volatility based strategy against a buy and hold approach. Figure 5 illustrates the equity curves of the volatility based CSA against the buy and hold strategy. Generally, the volatility based CSA produces visually superior results, when compared to the buy and hold. Due to the volatility-based strategy's utilization of a forward-looking index, and the strategy's ability to more accurately predict daily market direction, the returns generated by the volatility based strategy are generally speaking, strikingly greater than the buy and hold approach.

In summary, the excess returns captured by the volatility based CSA against a buy and hold strategy, for every equity index, with and without accounting for dividends and/or transaction costs, are all abnormally distributed, each with a mean that is statistically insignificantly different than zero. The volatility based CSA, although generally able to outperform a buy and hold trading strategy, is unable to produce statistically significant excess returns against a buy and hold strategy. Although, the results are statistically insignificant, the volatility-based strategy is generally able to outperform a buy and hold approach, not only across the entire sample period, but also when several sub-periods are analyzed as well. Lastly, it appears that generally, both the equity based and volatility based Combined Signal Approach generate statistically significantly superior risk adjusted returns versus a buy and hold strategy. This fact helps give credence to technical analysis as a dependable technique for equity investing.

CHAPTER 7

CONCLUSION

The Combined Signal Approach, one of the most successful technical trading strategies, has historically been able to offer consistently positive excess returns against the buy and hold strategy, when applied to the equity markets. One success of the volatility based Combined Signal Approach in this study is its ability to generate statistically significantly superior risk adjusted returns over a Buy and Hold Strategy, in all cases except the Nasdaq Composite, after accounting for both dividends and transaction costs. The Combined Signal Approach is applied uniquely in this study, each technical signal within the Combined Signal acts as a vote, from which a buy/sell signal is initiated. When utilized in this way, however, the Combined Signal Approach was unable to generate statistically significantly different than zero excess returns. This study is the first to test the Combined Signal Approach on a group of implied volatility indices in order to day trade each volatility index's underlying stock index. This study is also the first to utilize a Reality Check Test to test for the statistical significance of excess Sharpe Ratios. While the Combined Signal Approach offers statistically insignificant excess returns, the volatility based CSA trading strategy does outperform a buy and hold strategy at capturing more risk efficient returns.

This paper seeks not only to capitalize on a technical strategy that may beat the stock market, but also to validate the utilization of implied volatility indices as predictive tools for

determining short term market direction. The volatility based CSA, on average, is more successful at correctly predicting the relevant equity index's daily up/down direction than the buy and hold strategy. The volatility based CSA also capitalizes on capturing superior risk adjusted returns than the buy and hold strategy, even after accounting for dividends and transaction costs. The Combined Signal Approach has an impressive track record based on previous studies, in this technical approach, when applied to volatility indexes, the CSA does predict daily market direction better than a buy and hold strategy, about 55% of the time, versus 53% of the time. Therefore, it appears that technical signals drawn from implied volatility indexes, are not only capable of offering higher risk adjusted returns, but are also able to predict market direction better than a buy and hold strategy, a strong indication against the Random Walk Hypothesis.

Further understanding of the utility of an asset's implied volatility for the purpose of day trading can be accomplished by testing the Combined Signal Approach on the implied volatilities of commodities: gold, oil, corn, and soybean futures contracts, all have an implied volatility index from which technical signals may be mined for the purpose of day trading the aforementioned futures contracts. The Combined Signal Approach also may benefit from the addition of other previously successful technical signals: The Relative Strength Index, chart patterns, CRISMA, Bollinger Bands, and/or genetic programming algorithms, can be added to the Combined Signal Approach in order to ascertain whether implied volatility is useful beyond extracting returns with lower volatility/higher consistency. An asset's implied volatility can be utilized to predict the asset's expected up/down price range. If the asset's price reaches within proximity of either the top or bottom of the expected price range, the asset's price is expected to pivot away from the boundary, and settle closer to the middle of the expected price range. This

specific forecasting power of an asset's implied volatility has yet to be tested, along with the numerous other abovementioned strategies/technical signals. None of the technical signals mentioned above have been tested on an asset's implied volatility, yet each one potentially threatens the validity of the Random Walk Hypothesis. In summary, the volatility based CSA implemented in this study is unable to fully dismiss the claim of the Random Walk Hypothesis, but the results of this study in fact validate technical analysis as a means of acquiring generally more consistent returns than a buy and hold strategy. The results of this study indicate that technical analysis does offer similar return performance to the buy and hold strategy, with significantly lower risk, even after accounting for dividends and transaction costs, which is noteworthy.

APPENDIX

Table 1: Trading Dates and Ticker Symbols*

Index	First Trading Date	Last Trading Date	Equity Index Ticker Symbols	Volatility Index Ticker Symbols
NASDAQ	07/27/01	04/06/15	.IXIC	VXN
S&P 500	10/17/91	04/06/15	.INX	VIX
S&P 100	10/18/87	04/06/15	SP100	VXO
DJIA	07/21/98	04/06/15	.DJI	VXD

*Note: All data is extracted from Google Finance.

Table 2: Annualized Returns and Standard Deviations for Different Trading Strategies*

Strategy	Index	Return Before Trans Costs	St. Dev Before Trans Costs	Return After Trans Costs	St. Dev After Trans Costs
Buy and Hold					
	NASDAQ	8.22%	25.00%	8.22%	25.00%
	S&P 500	9.20%	18.00%	9.20%	18.00%
	S&P 100	7.20%	21.00%	7.20%	21.00%
	DJIA	6.27%	19.00%	6.27%	19.00%
Volatility CSA					
	NASDAQ	0.40%	21.30%	-4.60%	21.30%
	S&P 500	33.50%	17.70%	28.50%	17.70%
	S&P 100	38.80%	18.50%	33.80%	18.50%
	DJIA	27.80%	18.90%	22.80%	18.90%
Equity CSA					
	NASDAQ	4.80%	21.30%	-0.20%	21.30%
	S&P 500	9.00%	17.70%	4.00%	17.70%
	S&P 100	8.60%	18.50%	3.60%	18.50%
	DJIA	9.00%	18.90%	4.00%	18.90%
Buy and Hold		Before Dividends	Before Dividends	After Dividends	After Dividends
	NASDAQ	8.22%	25.00%	9.22%	25.00%
	S&P 500	9.20%	18.00%	11.00%	18.00%
	S&P 100	7.20%	21.00%	9.20%	21.00%
	DJIA	6.27%	19.00%	8.77%	19.00%

*Note: NASDAQ data are from 7-27-2001 to 4-6-2015, S&P500 data are from 10-17-1991 to 4-6-2015, S&P100 data are from 10-18-1987 to 4-6-2015, and DJIA data are from 7-21-1998 to 4-6-2015

Table 3: Sub-Period Analysis of Annualized Returns Before Dividends and Transaction Costs for Different Trading Strategies

Strategy	Index	Return 2001-2007	Return 2008-2009	Return 2010-2015
Buy and Hold				
	NASDAQ	4.30%	2.00%	15.00%
	S&P500	3.00%	-7.50%	12.50%
	S&P100	1.00%	-10.00%	10.00%
	DJIA	3.50%	-7.50%	10.00%
Volatility CSA				
	NASDAQ	-2.70%	-4.70%	8.50%
	S&P500	21.00%	11.20%	31.70%
	S&P100	28.00%	19.00%	38.10%
	DJIA	24.00%	11.10%	29.60%
Equity CSA				
	NASDAQ	-1.40%	-3.30%	10.20%
	S&P500	5.60%	5.10%	15.30%
	S&P100	2.30%	-9.10%	11.40%
	DJIA	5.40%	-6.20%	11.90%

Table 4: Trading Strategy Comparison

Index	Volatility Based CSA	Equity Based CSA	Buy and Hold
	Number of Trades	Number of Trades	Number of Trades
NASDAQ	3589	3589	3589
S&P500	6109	6109	6109
S&P100	7121	7121	7121
DJIA	4398	4398	4398
	Average Trade P/L	Average Trade P/L	Average Trade P/L
NASDAQ	\$0.16	\$1.90	\$3.25
S&P500	\$13.30	\$3.57	\$3.65
S&P100	\$15.40	\$3.41	\$2.85
DJIA	\$11.03	\$3.52	\$2.46
	Median Trade P/L	Median Trade P/L	Median Trade P/L
NASDAQ	\$6.75	\$7.54	\$9.12
S&P500	\$8.73	\$5.56	\$5.23
S&P100	\$9.52	\$5.16	\$5.95
DJIA	\$7.94	\$5.41	\$4.36
	Largest Winner	Largest Winner	Largest Winner
NASDAQ	7.00%	16.10%	23.00%
S&P500	9.00%	10.70%	14.00%
S&P100	21.00%	11.00%	15.00%
DJIA	7.40%	10.80%	11.00%
	Largest Loser	Largest Loser	Largest Loser
NASDAQ	-16.00%	-7.60%	-9.03%
S&P500	-10.00%	-8.70%	-9.01%
S&P100	-10.80%	-21.20%	-5.10%
DJIA	-10.90%	-7.70%	-7.80%

Table 4(continued): Trading Strategy Comparison

	Percent Winners	Percent Winners	Percent Winners
NASDAQ	53.30%	53.50%	53.80%
S&P500	55.20%	53.10%	53.40%
S&P100	55.50%	52.90%	53.10%
DJIA	54.80%	52.80%	52.40%
	Percent Losers	Percent Losers	Percent Losers
NASDAQ	46.70%	46.50%	46.20%
S&P500	44.80%	46.90%	46.60%
S&P100	44.50%	47.10%	46.90%
DJIA	45.20%	47.20%	47.60%
	Ann. Sharpe Ratio	Ann. Sharpe Ratio	Ann. Sharpe Ratio
NASDAQ	-0.22	-0.01	0.37
S&P500	1.61	0.23	0.61
S&P100	1.83	0.19	0.44
DJIA	1.21	0.21	0.46
	Max Drawdown	Max Drawdown	Max Drawdown
NASDAQ	\$5,663.00	\$7,600.00	\$9,030.00
S&P500	\$10,000.00	\$8,700.00	\$9,010.00
S&P100	\$10,800.00	\$21,200.00	\$5,010.00
DJIA	\$10,900.00	\$7,700.00	\$7,800.00
	Max Equity	Max Equity	Max Equity
NASDAQ	\$15,392.00	\$14,985.00	\$23,403.00
S&P500	\$4,378,027.00	\$18,366.00	\$94,309.00
S&P100	\$21,710,624.00	\$15,233.00	\$134,430.00
DJIA	\$275,621.00	\$18,812.00	\$33,870.00

Table 4(continued): Trading Strategy Comparison*

	Min Equity	Min Equity	Min Equity
NASDAQ	\$10,000.00	\$7,403.00	\$5,554.00
S&P500	\$10,000.00	\$7,171.00	\$10,000.00
S&P100	\$10,000.00	\$4,955.00	\$10,000.00
DJIA	\$8,460.00	\$10,000.00	\$10,000.00
	Ending Equity	Ending Equity	Ending Equity
NASDAQ	\$840.00	\$8,422.00	\$23,403.00
S&P500	\$4,378,000.00	\$18,366.00	\$94,309.00
S&P100	\$18,206,600.00	\$15,233.00	\$134,430.00
DJIA	\$275,000.00	\$17,552.00	\$33,870.00
	Ann. Average Return	Ann. Average Return	Ann. Average Return
NASDAQ	-4.60%	-0.20%	9.22%
S&P500	28.50%	4.00%	11.00%
S&P100	33.80%	3.60%	9.20%
DJIA	22.80%	4.00%	8.77%
	Ann. St Dev	Ann. St Dev	Ann. St Dev
NASDAQ	21.30%	21.30%	25.00%
S&P500	17.70%	17.70%	18.00%
S&P100	18.50%	18.50%	21.00%
DJIA	18.90%	18.90%	19.00%

*Note: Performance calculated after transaction costs and dividends factored in.

Table 5: Normality Test Results for Different Trading Strategies' Excess Returns

Strategy	Index	Jarque-Bera Test Statistic	Chi-Squared Distribution's Critical Value
Volatility CSA			
	NASDAQ	6237.06	124.30
	S&P500	7622.13	124.30
	S&P100	113375.59	124.30
	DJIA	4760.05	124.30
Equity CSA			
	NASDAQ	6169.82	124.30
	S&P500	7291.34	124.30
	S&P100	112301.47	124.30
	DJIA	4354.58	124.30

Table 6: Simulated Excess Returns, (Volatility CSA Returns Less Buy and Hold Returns)*

Index	Simulated Excess Return	Simulated Excess Return
	Mean of Means	Mean of St Dev
NASDAQ	-14.00%	39.40%
S&P500	18.80%	26.40%
S&P100	19.70%	34.44%
DJIA	12.00%	27.10%

*Note: Simulation Data created utilizing the Moving Block Method for Bootstrapping.

Results Presented in Table 6 are computed after factoring in Transaction Costs and Dividends.

Table 7: White's Reality Check Two-Tailed Z Test Statistic

Index	Volatility CSA Z Test Statistic	Corresponding P-Value
NASDAQ	-0.39	0.69
S&P500	0.62	0.54
S&P100	0.78	0.44
DJIA	0.49	0.62
	Simulated Volatility CSA Z Test Statistic	Corresponding P-Value
NASDAQ	-0.36	0.72
S&P500	0.73	0.47
S&P100	0.59	0.56
DJIA	0.44	0.66
	Simulated Excess Sharpe Ratio Z Test Statistic	Corresponding P-Value
NASDAQ	-1.67	0.09
S&P500	8.33	<1.0E-5
S&P100	11.88	<1.0E-5
DJIA	5.33	<1.0E-5

*Note: Statistics computed after Transaction Costs and Dividends have been factored in.

The Simulated Volatility CSA Z Test Statistics and Simulated Excess Sharpe Ratio Z Test Statistics are based off of the Excess Return, (Volatility CSA Return Less Buy and Hold Return), Moving Block Bootstrapping Simulation.

Table 8: Annualized Excess Sharpe Ratio, Volatility CSA Sharpe Ratio Less Buy and Hold Sharpe Ratio*

Index	Annualized Excess Sharpe Ratio	Simulated Mean Excess Sharpe Ratio	Simulated St Dev Excess Sharpe Ratio
NASDAQ	-0.39	-0.25	0.15
S&P500	0.61	0.75	0.09
S&P100	0.78	0.95	0.08
DJIA	0.48	0.64	0.12

*Note: Annualized Excess Sharpe Ratios are computed after considering Transaction Costs and Dividends

Simulated Excess Sharpe Ratio Parameters are derived from the same Moving Block Bootstrapping Simulation as the Parameters from Table 6.

Table 9: Simulated Sub-Period Annualized Excess Returns*

Strategy	Index	Simulated Excess Return 2001-2007	Simulated Excess Return 2008-2009	Simulated Excess Return 2010-2015
Volatility CSA				
	NASDAQ	-5.60%	-4.60%	-6.30%
	S&P500	17.90%	19.10%	18.50%
	S&P100	25.20%	26.80%	28.50%
	DJIA	22.50%	18.40%	22.60%
Equity CSA				
	NASDAQ	-7.20%	-4.00%	-6.20%
	S&P500	1.50%	15.20%	5.50%
	S&P100	1.40%	3.10%	0.70%
	DJIA	0.50%	2.00%	1.90%

*Note: Simulated Excess Returns are derived from a Moving Block Bootstrapping Simulation of Annualized Excess Returns, (CSA Return Less Buy and Hold Return)

*Note: Statistics computed before Transaction Costs and Dividends have been factored in.

Table 10: White's Reality Check Two-Tailed Z Test Statistic*

Index	Z Test Statistic	Z Test Statistic	Z Test Statistic	P-Value	P-Value	P-Value
	2001-2007	2008-2009	2010-2015	2001-2007	2008-2009	2010-2015
NASDAQ	-0.280	-0.230	-0.315	0.779	0.818	0.752
S&P500	0.895	0.955	0.925	0.370	0.319	0.355
S&P100	1.260	1.340	1.425	0.207	0.180	0.154
DJIA	1.125	0.920	1.130	0.260	0.358	0.258
Index	Z Test Statistic	Z Test Statistic	Z Test Statistic	P-Value	P-Value	P-Value
	2001-2007	2008-2009	2010-2015	2001-2007	2008-2009	2010-2015
NASDAQ	-0.360	-0.200	-0.310	0.718	0.841	0.756
S&P500	0.075	0.760	0.275	0.940	0.447	0.783
S&P100	0.070	0.155	0.035	0.944	0.877	0.972
DJIA	0.025	0.100	0.095	0.980	0.920	0.924

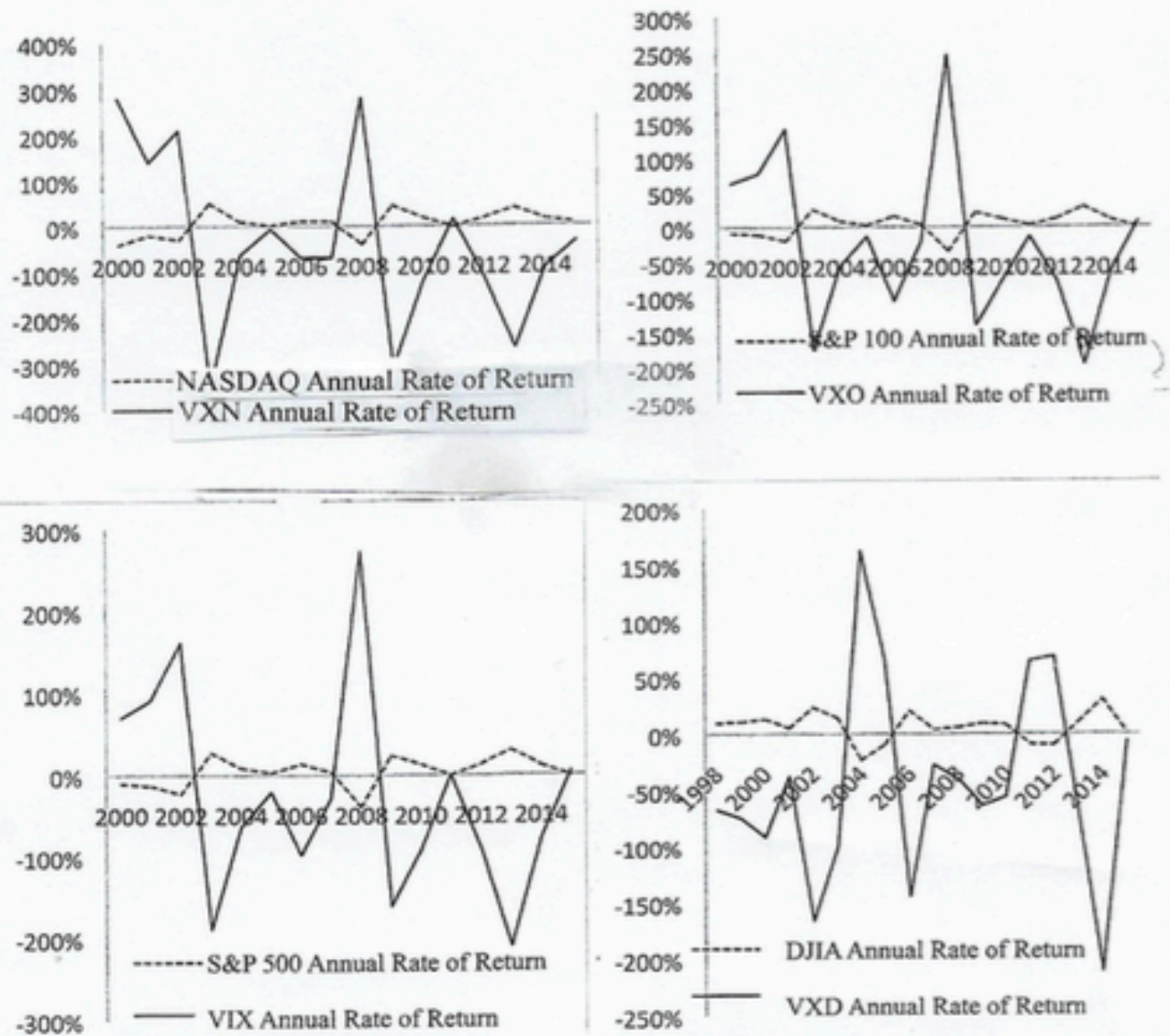
*Note: Top: Volatility CSA Returns Less Buy and Hold Returns

Bottom: Equity CSA Returns Less Buy and Hold Returns

Statistics computed before Transaction Costs and Dividends have been factored in.

Figure 1

Equity Index & Corresponding Volatility Index Annual Performance Relationship



*Note: Google Finance: Historical Quotes .IXIC and VXN, .INX and VIX, SP100 and VXO, .DJI and VXD

Figure 2

Annual Rate of Return Volatility Based CSA Strategy Comparison

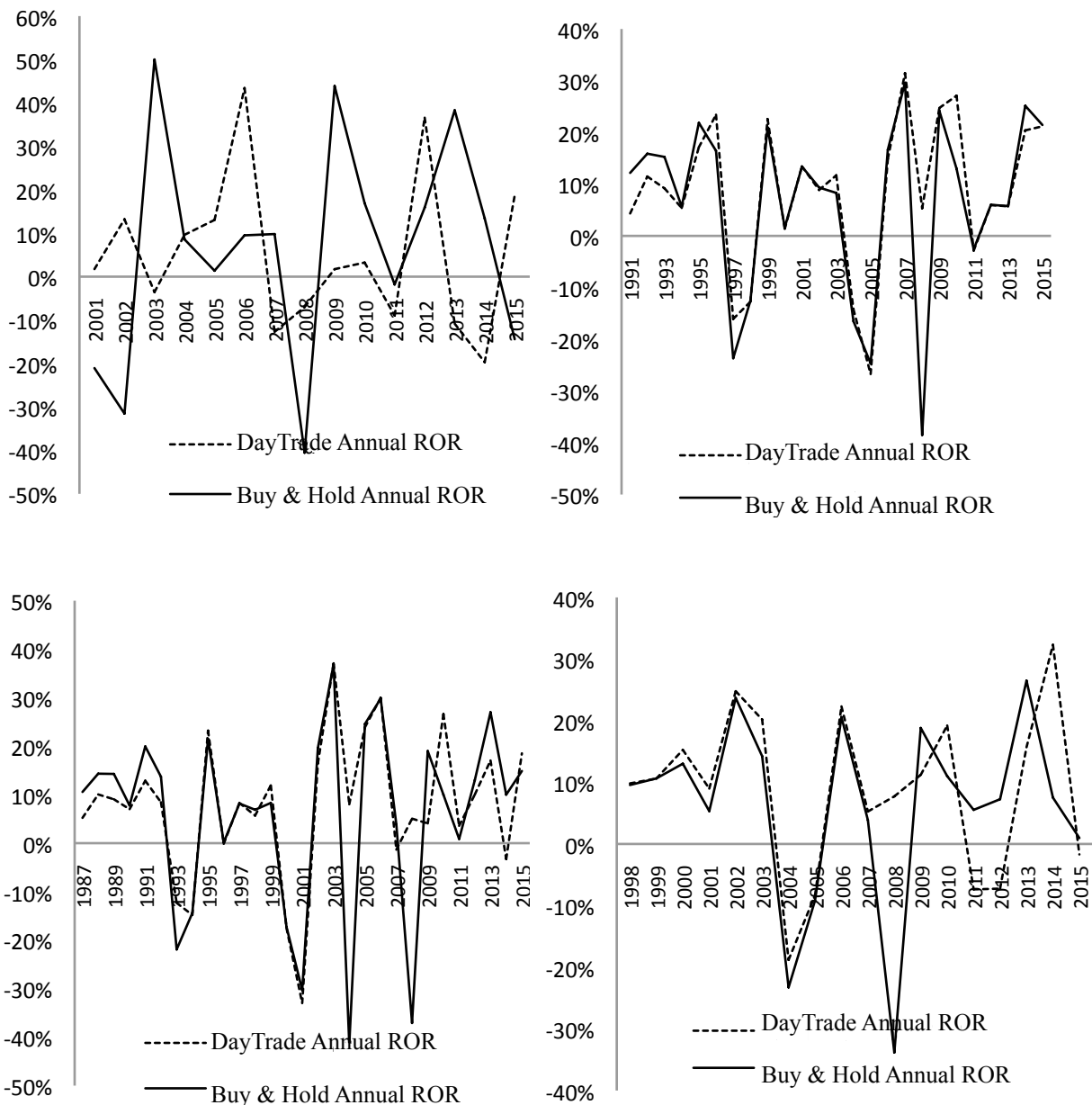


*Note: Google Finance: Historical Quotes: .IXIC, .INX, SP100, and .DJI

Top Left: Nasdaq, Top Right: S&P 500, Bottom Left: S&P 100, Bottom Right: DJIA

Figure 3

Annual Rate of Return Equity Based CSA Strategy Comparison

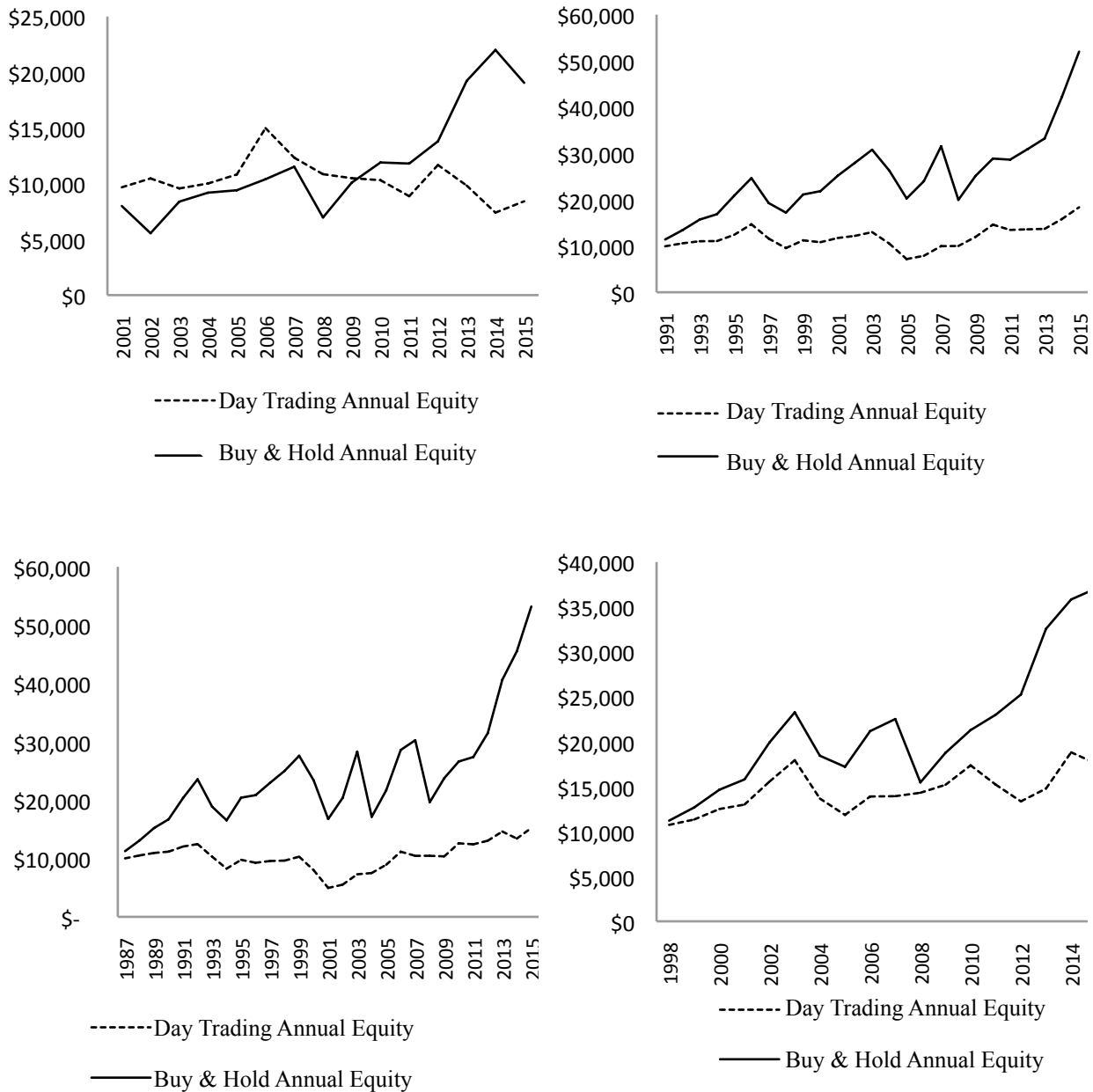


*Note: Google Finance: Historical Quotes: .IXIC, .INX, SP100, and .DJI

Top Left: Nasdaq, Top Right: S&P 500, Bottom Left: S&P 100, Bottom Right: DJIA

Figure 4

Equity Curve Equity Based CSA Strategy Comparison

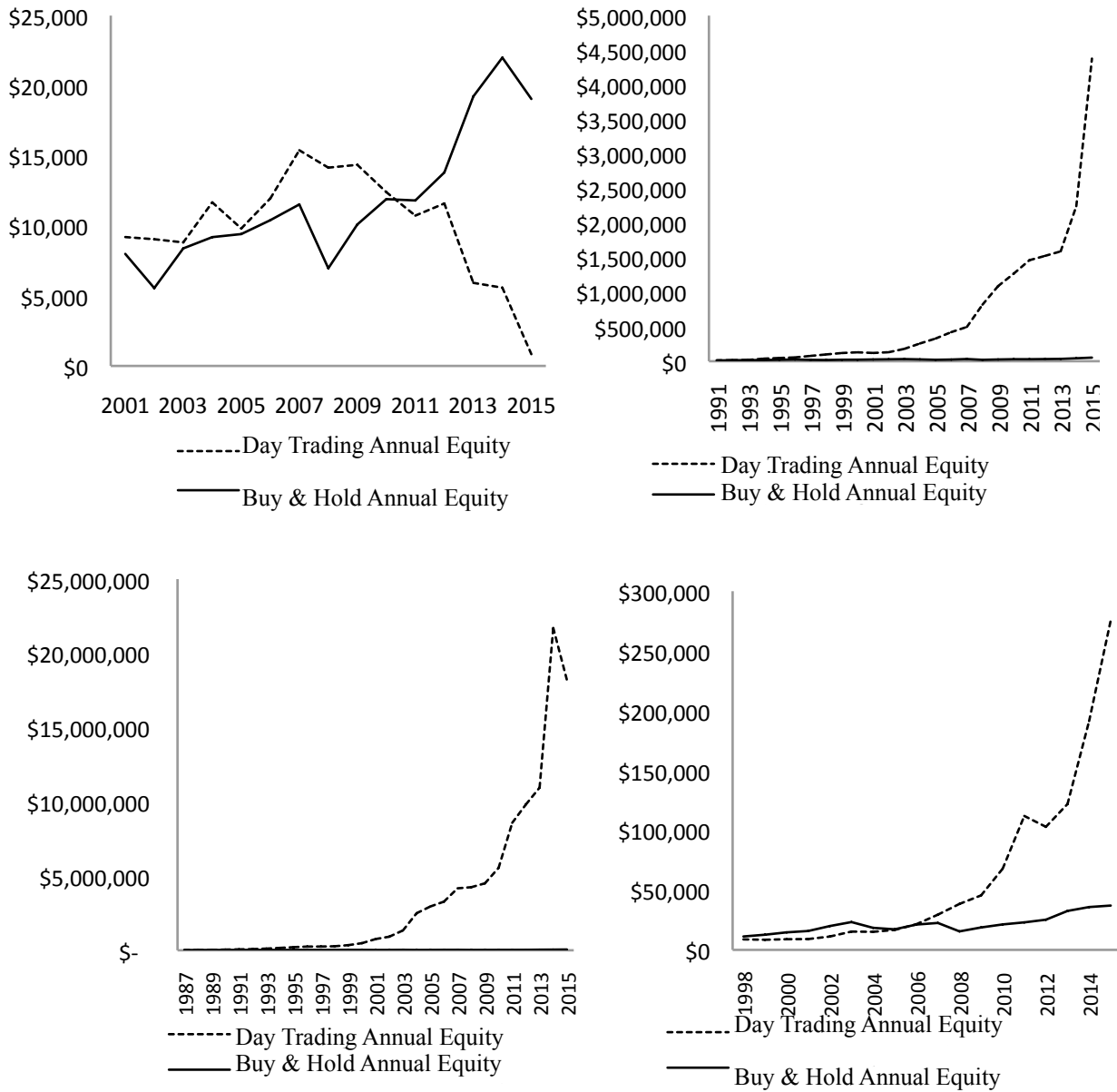


*Note: Google Finance: Historical Quotes: .IXIC, .INX, SP100, and .DJI

Top Left: Nasdaq, Top Right: S&P 500, Bottom Left: S&P 100, Bottom Right: DJIA

Figure 5

Equity Curve Volatility Based CSA Strategy Comparison



*Note: Google Finance: Historical Quotes: .IXIC, .INX, SP100, and .DJI

Top Left: Nasdaq, Top Right: S&P 500, Bottom Left: S&P 100, Bottom Right: DJIA

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